PPL
7/24/08
1:50 pm

Asymmetric Information between Employers* [Job Market Paper]

Lisa B. Kahn†
Harvard University

November 14, 2007

Abstract

Employer learning about workers' abilities plays a key role in determining how workers sort into jobs and are compensated. This study explores whether learning is symmetric or asymmetric, i.e., whether potential employers have the same information about worker ability as the incumbent firm. I develop a model of asymmetric learning that nests the symmetric learning case and allows the degree of asymmetry to vary. I derive testable implications for the prevalence of asymmetric learning involving a new dependent variable: the variance in pay changes. Using the NLSY, I employ three distinct identification strategies to test different predictions of the model. I first test whether laid-off workers appear negatively selected compared to workers who lost jobs in plant closings, by comparing the variances in pay changes at their new jobs. I next exploit the fact that groups of workers differ in their variances in ability – based on economic conditions at time of entry into a firm – to show that incumbent wages track ability more closely than do outside firm wages. Finally, I provide additional evidence using the fact that learning about ability is more symmetric for some occupations than for others. All three cases favor the asymmetric learning model and suggest that the effect on wage setting is significant both statistically and in terms of economic magnitudes.

*I am grateful to George Baker, John Beshears, Richard Freeman, John Friedman, Carola Frydman, Bob Gibbons, Tal Gross, Naomi Hausman, Richard Holden, Guido Imbens, Radha Iyengar, Karthik Kalyanaraman, Steve Levitt, Emily Oster, Josh Schwartzstein, Mike Waldman, seminar participants at Harvard University and especially Larry Katz, Claudia Goldin and Caroline Hoxby for helpful comments and guidance.

†Correspondence: Lisa Kahn, NBER, 1050 Massachusetts Ave, Cambridge, MA 02138. Email: lisakahn@fas.harvard.edu

1 Introduction

The sorting of workers into firms is an important aspect of the labor market. A significant part of this sorting involves both worker and firm learning about the quality of workers over time. For example, many patterns observed in the job mobility literature – that young workers change jobs often (Topel and Ward 1992) yet long-term employment relationships are common and the probability of remaining at a firm rises with tenure (Farber 1999) – are consistent with employer learning over time about overall or match-specific worker quality. However, the extent to which information about workers spreads across the market is less clear. Asymmetric information exists when incumbent employers have more information about worker quality than potential employers do. Consider a team of research assistants working for a professor. The professor can see exactly which worker performed each task and who contributed important ideas, yet the outside world observes only what appears on the bottom of an academic paper: the professor is grateful for the excellent research assistance of....

Under asymmetric information, inefficiencies can arise in both allocating workers to jobs and investing in worker human. Waldman's 1984 model assumes that outside firms can observe promotions but not wages and implies that a worker's outside option changes sharply upon promotion.[1] The incumbent firm must offer a large wage increase to keep the worker so there are fewer promotions than would be optimal.[2] Turning to human capital, several

[1] Other papers focusing on the promotion-as-signal hypothesis include Bernhardt (1995) which contains an extended version of the Waldman (1984) model with more empirical predictions and Zabojnik and Bernhardt (2001) which brings tournament theory and general human capital investment into the model.

[2] Similarly, Milgrom and Oster (1987) hypothesize that skills of minority workers are difficult for outside firms to discern, but promotions allay this problem by increasing observability. Firms thus underpromote minority workers to retain their informational advantage.

theoretical papers point out that under asymmetric information, workers could underinvest in general skills.[3] When outside firms cannot observe workers' investments, the incumbent firm need not fully compensate the worker.[4] It is necessary to understand the importance of asymmetric information to know whether these inefficiencies should be of concern.

This paper seeks to identify whether asymmetric information is prevalent in the labor market. Since promotions and non-schooling human capital investment are difficult to observe in standard data sets, I develop a methodology that uses wages to identify the existence of asymmetric information. I derive a model that allows the degree of asymmetry to vary and nests symmetric learning as a special case, as follows. Assume workers have some degree of unobserved ability. At the point of entry, workers are paid identically, conditional on the component of ability that the firm observes. Once a worker is hired, the incumbent firm learns about the worker's initially unobserved ability. Some portion of firm learning is reflected in the wage. The distribution of wages within a firm, in consequence, becomes more dispersed over time as employee tenure increases. Wage changes, reflecting how much an employer has learned between periods, also spread out. Further, the distribution of wage changes track the distribution of initially unobserved ability, implying that the variance in wage changes is increasing in the variance in ability.

I employ three identification strategies that test different implications of the model, using the National Longitudinal Survey of Youth. First, the asymmetric information model implies that lower-ability workers are more likely to leave the firm (Greenwald (1986) and Gibbons

[3] See, for example, Chang and Wang (1996), Katz and Ziderman (1990) and Waldman (1990).

[4] Alternatively, Acemoglu and Pischke (1998) show that under asymmetric information it might be optimal for firms to provide general training to workers because, by selecting into a firm that provides general training, workers can signal that they are high quality.

and Katz (1991)) since the incumbent employer but not the outside employer has learned that they are low ability. I test this prediction by comparing employer learning at the next job of endogenous versus exogenous movers; under asymmetric information, endogenous movers will have a lower variance in ability. Following Gibbons and Katz (hereafter GK), I exploit plant closings as a plausibly exogenous event forcing workers to switch jobs.[5] Consistent with the asymmetric learning model, I find that wage changes at a new employer are more spread out for workers who lost jobs due to plant closings than for laid-off workers.

The second identification strategy tests comparative statics on the variance in ability of cohorts of workers. Under asymmetric information, outside firms update less on initially unobserved ability than incumbent firms do. Thus for movers relative to stayers, the wage change (defined for movers as the first wage at the new firm minus the last wage at the old firm) will be less linked to ability. In particular, the variance of wage changes for movers will be less related to the variance in initially unobserved worker ability.

For cross-group differences in the variance in worker ability I use labor market conditions at time of entry into a firm. I show that workers who enter firms in recessions have *lower* variance in ability than workers who enter firms in booms. During a recession, the share of job-seekers who are unemployed or leaving bad jobs increases relative to boom-times; those workers with better jobs quit less frequently because they are less likely to find a better opportunity elsewhere. In consequence, the variance of worker ability will be lower for workers who enter firms in recessions – these workers are more likely to be of lower quality.[6]

[5] GK hypothesize that if learning is asymmetric, being laid off should be a negative signal of ability whereas there should be no stigma associated with losing a job due to a plant closing. Using data from the CPS Displaced Workers Survey, they show that laid off workers pay a larger wage penalty at a new job, relative to workers who lost their jobs due to plant closings.

[6] Workers who enter firms in recessions will also have a lower mean of ability. However, I show below

Consistent with their lower variance in ability, workers who enter firms in recessions do indeed have a lower variance in wage changes within the firm but not when they subsequently switch firms. This finding supports the asymmetric learning model because it indicates that outside wage offers are less linked to ability.

The third identification strategy tests comparative statics over the degree of asymmetry in the market. I show that in a highly symmetric market, wages should track ability more closely so that the variance in pay changes will be larger than in an asymmetric market. This result will hold for the pay changes of both workers who stay at a firm and workers who move, but the effect will be larger for movers. Because, by definition, the degree of asymmetry affects the information of outside firms more than that of incumbents, it will also affect outside wage offers more.

As a source of variation in asymmetry, I compare workers across job types that vary in the degree to which performance is observable outside the firm. I hypothesize that the work of managers and professionals in non-service industries (e.g. corporate lawyers and programmers) is less observable to outside employers than that of professionals in service industries (e.g. private practice lawyers and consultants) because service industries involve frequent client interaction. I provide support for this claim both from previous literature and in these data. I find that, consistent with my asymmetric information model, the variance in wage changes is smaller in the more asymmetric markets but that the relationship between variance and asymmetry is smaller in magnitude for stayers.

Each of the three approaches I use may have confounding factors; I address several of these. In particular, I conclude that human capital investment, differential turnover and

---

that this does not affect the predictions of the model.

differences in match quality are most likely not confounding factors. Though each of the three strategies has its own set of potential issues, all consistently yield the same results.

The idea of asymmetric information between employers is intuitive, yet little empirical evidence exists. Several papers use AFQT score to provide evidence that employer learning is indeed prevalent, but they assume that learning is symmetric across employers.[7] A few papers provide empirical support for asymmetric learning but usually require strong assumptions or look in specialized settings.[8] Schönberg (2007), the closest to the current paper, exploits the methodology developed in the symmetric-learning literature, also using the NLSY. For college graduates the relationship between AFQT score and earnings is increasing in tenure at a firm, controlling for the increased effect of AFQT score across levels of experience, implying that incumbent employers learn more about productivity than the rest of the market.[9]

The advantages of this paper are several. It contributes new a methodology for identifying employer learning, complementary to the previous literature. This methodology can be used in a variety of settings beyond those studied here. Further, the use of second moments allows me to test comparative statics that were not possible in the previous literature, across a broad range of jobs and workers. I conclude that asymmetric information between

[7] In their canonical paper, Farber and Gibbons (1996) argue that the Armed Forces Qualifying Test (AFQT), administered to respondents in the NLSY in 1980, is unobservable to employers yet highly correlated with ability. They show that the effect of AFQT on wages becomes stronger over time and that of education becomes weaker, providing evidence that employers learn about worker ability. Altonji and Pierret (2001) expand this methodology to study statistical discrimination and Lange (2007) provides an estimate for the speed of employer learning.

[8] In addition to GK, DeVaro and Waldman (2004) test an extended version of the Waldman (1984) model, using proprietary data from a single firm, and find support for asymmetric information. Using data on apprentices in Germany, Acemoglu and Pischke (1998) link employer-provided training to asymmetric information and von Wachter and Bender (2006) show that workers released by firms are negatively selected.

[9] However, Schönberg finds no evidence for asymmetric learning among high school graduates. See the conclusion for a discussion of this.

employers is prevalent in the labor market and that the effects are large in magnitude.

The remainder of the paper proceeds as follows. Section 2 presents a theoretical model with empirical predictions to be tested in the paper. Section 3 describes the data and the empirical methodology, which is largely unified across strategies. Section 4 presents the results and shows that the asymmetric information model is supported in all three empirical strategies. Section 5 discusses alternative explanations, and section 6 concludes.

2 Theory

2.1 Basic Setup and Timing

To illustrate the comparative statics used in this paper, consider the following 2-period model. Worker i has unobserved ability μ_i – that is, residual ability after conditioning on observable characteristics (such as education) at the beginning of period 1 – drawn from a distribution with cumulative distribution and probability density functions $\Phi(\mu)$ and $\phi(\mu)$. To simplify the analysis, I assume that ability is normally distributed, i.e., $\phi(\cdot) \sim N(m, \sigma^2)$. I also assume that output equals ability in all firms in all periods. Thus, there is no matching or comparative advantage and there is no training or human capital investment after labor market entry. These assumptions simplify the analysis though I discuss their effect on the results below. In the first period, μ is unknown to all parties: both workers and firms. In period 1 firms hire workers; call the hiring firm the incumbent. The wage in the first period, w_0, satisfies a zero-profit condition for the firm. During period 1 the incumbent firm learns the worker's initially unobserved ability perfectly and offers a period 2 wage.

I assume that outside employers cannot observe worker ability or period 2 wage offers. Instead, suppose that at the end of period 1, they observe a public, noisy signal of ability for each worker, s_i. Let $s_i = \mu_i + \epsilon_i$ where $\epsilon \sim N(0, r\sigma^2)$, $r \geq 0$ and ϵ is independent of μ. If $r = 0$ then $s = \mu$ with certainty and we are in the perfectly symmetric learning case. As r approaches ∞, the signal becomes meaningless and we approach the perfectly asymmetric learning case. I assume the incumbent firm and the worker also observe s.[10] The incumbent firm's strategy is a mapping $w(\mu, s) : \mathbb{R}^2 \longrightarrow \mathbb{R}$ while an outside firm's strategy is a mapping $v(s) : \mathbb{R} \longrightarrow \mathbb{R}$, both yielding period 2 wage offers.

Mobility is driven by a random disutility shock, θ, which workers observe at the end of period 1 (following Acemoglu and Pischke 1998). I assume θ is uniformly distributed over the interval $[-\bar{\theta}, \bar{\theta}]$ and is independent of μ and s. It is the worker's ex-post evaluation of the workplace (e.g., the worker's dislike of coworkers) and is meant to represent the level of random turnover in the economy. Workers maximize income minus the disutility shock. Also, neither incumbent nor outside firms can observe a given worker's θ.[11]. The worker's strategy is therefore a decision rule; based on w, v, and θ, the worker chooses to stay or move.

To summarize, the timing of events is as follows: At the beginning of period 1, workers randomly match to firms and earn a wage, w_0. At this point, information is symmetric in that firms and workers do not know unobserved ability (i.e., residual ability after conditioning on observables). Production takes place during period 1 and incumbent firms perfectly learn

[10]This approach draws on Schönberg (2007), although her model has only two types of workers and a binary signal to outside employers. Pinkston (2005) derives a learning model with private signals and focuses on raids and bidding wars.

[11]I could instead assume that firms observe θ but cannot react to it by changing their wage offers.

the previously unobserved component of ability. Outside firms, in contrast, observe s, a noisy signal of unobserved ability. At the end of period 1, firms make wage offers based on the new information. Workers then observe their utility shock and decide whether to stay or leave. In the second period workers earn either the incumbent firm's wage offer or the outside wage offer and then they retire.

2.2 Calculating the Equilibrium

The Perfect Bayesian equilibrium consists of an incumbent firm wage schedule, $w^*(\mu, s)$, an outside firm wage schedule, $v^*(s)$, and the worker's quit decision, such that: (1) the incumbent firm maximizes profits conditional on outside firm behavior, (2) outside firms maximize profits subject to beliefs about worker turnover behavior, (3) workers maximize income minus θ in making their quit decision and (4) all beliefs are consistent with these strategies.

The worker chooses to stay at the firm if $w(\mu, s) - \theta > v(s)$. Equation 1 is the probability that the worker stays conditional on μ and s.

$$\Pr(stay|\mu, s) = \frac{w(\mu, s) - v(s) + \bar{\theta}}{2\bar{\theta}} \tag{1}$$

Denote the equilibrium outside wage offer as $v^*(s)$. The incumbent firm takes outside firms' behavior as given and maximizes the expected profit for each ability type, μ, and realization of s (shown in appendix A.1). The optimal wage schedule is then given in equation 2.

$$\max_{w(\mu,s)} (\mu - w(\mu,s)) * \Pr(stay|\mu,s)$$
$$\implies w^*(\mu,s) = \frac{1}{2}(v^*(s) + \mu - \bar{\theta}) \tag{2}$$

First, note that $w^*(\mu,s)$ is increasing in μ. Therefore, the probability of staying at a firm is also increasing in μ. Higher wage offers from the incumbent firm are more likely to outweigh the disutility shock, θ. Thus the model yields the classic lemons effect (a la Greenwald (1986) and GK) that worse workers are more likely to leave.

Outside firms set a wage schedule, $v(s)$, equal to expected productivity conditional on leaving the firm and on s.[12] Bayes' rule yields the following expression, where $\pi(.)$ is the posterior pdf of μ conditional on s.

$$v^*(s) = E(\mu|\text{move}) = \frac{\int_{-\infty}^{\infty} \mu * (1 - \Pr(\text{stay}|\mu,s)) * \pi(\mu|s) d\mu}{1 - \Pr(stay|s)}$$

The system of equations can be solved and yield the solutions for $v^*(s)$, $w^*(\mu,s)$ and

[12] The wage offer will converge on expected productivity if outside firms undergo Bertrand competition, for example.

$\Pr(stay|\mu, s)$ shown in equations 3-5 (see appendix A.1 for the derivation of $v^*(s)$).[13]

$$
\begin{aligned}
v^*(s) &= \frac{mr+s}{1+r} - \frac{3}{2}\bar{\theta} + \sqrt{\frac{9}{4}\bar{\theta}^2 - \frac{r\sigma^2}{1+r}} && (3)\\
w^*(\mu, s) &= \frac{1}{2}(\mu + \frac{mr+s}{1+r} - \frac{5}{2}\bar{\theta} + \sqrt{\frac{9}{4}\bar{\theta}^2 - \frac{r\sigma^2}{1+r}}) && (4)\\
\Pr(stay|\mu, s) &= \frac{1}{4\bar{\theta}}(\mu - \frac{mr+s}{1+r} + \frac{5}{2}\bar{\theta} - \sqrt{\frac{9}{4}\bar{\theta}^2 - \frac{r\sigma^2}{1+r}}) && (5)
\end{aligned}
$$

Finally, the period 1 wage can be calculated by adding a zero ex–ante profit condition. This is done in appendix A.2. Since at the beginning of period 1 ability is unknown, w_0 is simply a constant (conditional on observable characteristics).

2.3 Comparative Statics

Case 1: Symmetric Information When $r = 0$, $v^*(s) = s$ (which equals μ exactly), $w^*(\mu, s) = \mu - \frac{\bar{\theta}}{2}$ and $\Pr(stay|\mu, s) = \frac{1}{4}$. First note that the probability of staying is not dependent on ability, so turnover is random. Therefore, the distribution of ability for movers equals the distribution of ability for the full group. Second, since the period 2 wage offer of incumbent and outside firms differs only by a constant, the variance in pay changes will be equal for movers and stayers. In fact, it equals σ^2 in both cases. Thus the variance in pay changes is perfectly linked to the variance in unobserved ability for both movers and stayers.

Case 2: Asymmetric Information The change in wages between periods 1 and 2 for workers who stay with the incumbent firm, Δw^{stay}, is by definition, $w^*(\mu, s) - w_0$. Equation 6

[13] It is desirable to place a condition on $\bar{\theta}$ so that a large proportion of ability types have positive probabilities of leaving the firm (obviously if $\mu = \infty$ the worker will never leave and if $\mu = -\infty$ the worker will never stay). A natural such condition is that the variance of θ be greater than the variance of μ, or $\frac{\bar{\theta}^2}{3} > \sigma^2$. If this is true then $\frac{9}{4}\bar{\theta}^2 - \frac{r\sigma^2}{1+r} > 0$ so v^* has only real solutions.

gives its variance, derived in appendix A.3. To learn about how the variance in wage changes for stayers is related to the variance in ability, we can take the derivative of equation 6 with respect to σ^2. In appendix A.3 I show that the derivative is always positive. Proposition 1 summarizes this result.

$$Var(\Delta w^{stay}) = \frac{1}{4}(\frac{4+r}{1+r}\sigma^2 - \frac{(\frac{r\sigma^2}{(1+r)})^2}{(\frac{5}{2}\bar{\theta} - \sqrt{\frac{9}{4}\bar{\theta}^2 - \frac{r\sigma^2}{1+r}})^2}) \tag{6}$$

Proposition 1 *The variance in wage changes of stayers is increasing in the variance in unobserved ability of the initial group of workers entering the firm. This is true under both symmetric and asymmetric learning.*

Using proposition 1, I now develop several implications of the model, each leading to a separate identification strategy.

Endogenous v Exogenous Movers Outside firms update on the quality of movers based on s and the fact that workers were willing to leave. Equation 7 shows the variance in ability of movers (derived in appendix A.4), which is clearly less than the variance in ability of the initial group, σ^2. The variance is lower because leavers are more likely to be lower-ability. However, note that when $r = 0$, i.e., when learning is perfectly symmetric, the variance in ability of movers equals σ^2 and movers are not selected. This result is summarized in proposition 2.

$$Var(\mu|move) = \sigma^2 - \frac{(\frac{r\sigma^2}{1+r})^2}{(\frac{3}{2}\bar{\theta} + \sqrt{\frac{9}{4}\bar{\theta}^2 - \frac{r\sigma^2}{1+r}})^2} < \sigma^2 \tag{7}$$

Proposition 2 *Under asymmetric learning (i.e., $r > 0$), the variance in unobserved ability of movers is less than the variance in unobserved ability of the initial group of entrants into the firm. Under symmetric learning, however, the variance in ability of movers equals the variance in ability of the initial group.*

To build intuition, imagine the following extension of the current model to 3 periods.[14] Suppose there exist two groups of workers. The first group, "layoffs", endogenously left their period 1 firm via the mechanism specified in the model. This group earns $v^*(s)$ in period 2 and because of logic similar to that which lies behind equation 7, this group's variance in ability is less than σ^2. The second group, "plant closings", exogenously left their initial firm due to a random shock. Since there was no selection involved, this group has a mean ability of m and a variance of σ^2 so workers earn w_0 in period 2. New firms learn about the ability of their workers between periods 2 and 3 and optimally offer a period 3 wage. We know from proposition 1 that the variance in the wage change between periods 3 and 2 (the second wage at the new firm minus the first wage at the new firm) will be increasing in the variance of the prior on ability and from proposition 2 that, when information is asymmetric, the variance of the prior on ability is smaller for layoffs than for plant closings. Thus, under asymmetric information, the variance in wage changes at the new firm will be smaller for layoffs than for workers displaced by plant closings in period 1.

Differences in σ^2 Next, returning to the 2-period model, we need to compare the variance in wage changes for stayers with the variance in wage changes for movers. The wage change for movers, Δw^{move}, is by definition, $v^*(s) - w_0$. Its variance, shown in equation

[14] A more formal analysis exists in an appendix available from the author upon request.

8 (and derived in appendix A.4), is related to ability, but only by a factor of $\frac{1}{1+r}$.

$$Var(\Delta w^{move}) = \frac{1}{1+r}\sigma^2 \tag{8}$$

As r increases, we approach the pure asymmetric case and the variance of wage changes of movers becomes unrelated to the underlying variance in ability.

We need to sign the following expression, comparing the relationship between the variance of wage changes and σ^2 for stayers with the relationship for movers.

$$\frac{\partial Var(\Delta w^{stay})}{\partial \sigma^2} - \frac{\partial Var(\Delta w^{move})}{\partial \sigma^2}$$

In appendix A.5, I show that the above is *positive*, i.e., the derivative is larger for the variance in wage changes of stayers than for movers. This result is intuitive since, under asymmetric information, the incumbent firm has learned more about worker ability so the distribution of wage changes can more closely track the distribution of ability. Proposition 3 summarizes this finding.

Proposition 3 *Under asymmetric information, the variance in wage changes for stayers responds more to changes in the underlying variance in unobserved ability than does the variance in wage changes for movers.*

Suppose there are two groups, one with a high variance in ability and one with a low variance in ability and that in each group some workers stay at their initial firm and some workers move, as described in the model above. We can then test proposition 3 with the following difference-in-differences estimate.

$$dd_\sigma = (var_s^l - var_s^h) - (var_m^l - var_m^h)$$

var is some measure of the spread of wage changes for a group, the subscript denotes whether the group stayed (s) or moved (m) and the superscript denotes the variance in ability (h for high and l for low). If asymmetric information is important, that is if $r > 0$, we should find that dd_σ is negative. That is, the decrease in the variance in wage changes seen in the low variance group compared to the high variance group is larger in magnitude for stayers than for movers. In contrast, under symmetric information, period 2 wage offers are equally linked to ability for both movers and stayers, so the variances in wage changes are equally linked to variance in ability and $dd_\sigma = 0$.

Differences in r Finally, we need to see how the variance in wage changes is affected by changes in r, the degree of asymmetry in the market. To do this, I take the derivative of equations 6 and 8 (the variances in wage changes for stayers and movers, respectively) with respect to r. These are derived in appendix A.6, where I also show that both expressions are always negative: The distributions of wage changes in more asymmetric markets are less spread out relative to those in more symmetric markets, for both movers and stayers. The intuition is that the outside wage offer, $v^*(s)$, is less related to true ability when information is more asymmetric. Since $v^*(s)$ is a component of period 2 wages for both movers and stayers, period 2 wages will be less linked to true ability, implying wage changes will be less dispersed.

We can now think about the relationship between the derivatives of the variances in wage changes with respect to the degree of asymmetry, r, for stayers and movers, expressed below.

$$\frac{\partial Var(\Delta w^{stay})}{\partial r} - \frac{\partial Var(\Delta w^{move})}{\partial r}$$

Appendix A.6 shows that the above expression is always *positive*. That is, the response of the variance in wage changes to a more asymmetric market is larger (in absolute value) for movers than for stayers. This is summarized in proposition 4. The result is intuitive because the variance for movers is entirely driven by variation in $v^*(s)$, which is only one component of the variance for stayers (recall from equation 2 that the period 2 wage for stayers is the average of true ability and $v^*(s)$).

Proposition 4 *The variances in wage changes for movers and stayers are smaller in more asymmetric markets but the variance in wage changes for movers responds more strongly to changes in r than does the variance for stayers.*

Suppose there are two types of occupations where the market for one can be identified as more asymmetric. We can again calculate a difference-in-differences estimator to test proposition 4.

$$dd_r = (var_s^A - var_s^S) - (var_m^A - var_m^S)$$

Here, the superscripts denote whether the group is in an asymmetric market (A) or a symmetric market (S) and the subscripts still denote whether the group stayed or moved. My asymmetric-learning model predicts that dd_r will be positive; the variance in wage changes for stayers responds less negatively to an increase in asymmetry than it does for movers.

3 Data and Methodology

All empirical approaches in this paper use the National Longitudinal Survey of Youth (NLSY) from 1979-2000 (details of which can be found appendix B). The sample is restricted to the male cross-section sample, omitting women and the over samples of blacks, Hispanics, military and poor whites.[15] The NLSY is particularly useful because it allows respondents to list up to five employers in the past year and these employer-employee relationships can be tracked across survey years. In addition, it allows me to follow a nationally representative group of workers over a long period of time. To be included in the sample a wage observation must reflect full-time, non-enrolled, non-self-employed, post-transition work.[16] Appendix table B1 provides more detailed variable descriptions and appendix table B2 shows sample sizes for all three analyses.

In each analysis, I estimate a first-stage regression of the form specified in equation 9.

$$Lwage_{igt} - Lwage_{ig,t-1} = \alpha_0 + \alpha_1' I_{ig}^{\text{group}} + \alpha_2' X_i + \alpha_3' Z_{igt} + \varepsilon_{igt} \tag{9}$$

For a worker, i, in group, g, and year t, I regress log wage change on a vector of group fixed effects, I_{ig}^{group}, and a set of control variables. The groups of interest, g, vary by

[15] Women are excluded because it is important to isolate workers with strong attachment to the labor market.

[16] Transition is defined similarly to Farber and Gibbons (1996) and Schönberg (2007) as primarily working (working full time for at least half the year) for two consecutive years. At the beginning of this two-year spell, the worker is assumed to be post-transition.

identification strategy as do the sample restrictions, and will be specified below. X_i is a vector of time-invariant controls including black, Hispanic and education dummy variables. Z_{igt} is a vector of time-varying controls which differs slightly across analyses but always includes the following: a quadratic in age, age in $t-1$, dummy variables for each year of tenure at time t, dummy variables for each year of tenure in $t-1$, change in squared tenure, geographic region and urban status, marital status, actual labor market experience before starting the current job, occupation and industry dummy variables, indicators for having changed occupation or industry and year dummies.[17] Table B3 provides summary statistics for each sample.

I then measure the spread of these log wage-change residuals for different groups with two dependent variables: the squared residuals and the inter-quartile range of the residuals. The variance of wage-change residuals for a particular group of workers, g, equals $E[\varepsilon_{igt}^2|g] - (E[\varepsilon_{igt}|g])^2$. The residuals are purged of group fixed-effects in the first-stage regression, so $E[\varepsilon_{igt}|g] = 0$. Thus the variance can be characterized by the ε_{igt}^2's.[18] Looking at wage-change residuals is instructive because it allows me to condition on characteristics the employer can observe at the start of the employment relationship. The residuals then yield information about the degree to which employers are learning about initially unobserved ability.[19]

[17] The layoffs analysis also includes time between the displaced job and the current and final tenure at the displaced job. Both the job-entry cohorts and occupations analyses include final tenure at the job held in $t-1$ if moved (otherwise 0). The occupations analysis additionally includes dummies for occupation in $t-1$ (the main groups), dummies for occupation in t and a full set of interactions.

[18] Using squared residuals allows me to exploit all variation in the micro data by keeping the unit of observation an individual-employer-year. However, results are similar when I collapse the data to the group level and estimate standard deviations.

[19] One might worry about variables the employer can observe but I, the econometrician, cannot, especially if they differ systematically across groups. This is not a problem as long as these variables are observed by all employers, in which case they are absorbed in the group fixed effect in the first stage. For example, if

To be precise, equation 10 shows the second-stage regression estimated for the layoffs analysis.

$$\varepsilon_{igt}^2 = \beta_0 + \beta_1' I_{i,g}^{\text{reason}} + \beta_2' X_i + \nu_{igt} \tag{10}$$

$I_{i,g}^{\text{reason}}$ is a vector of indicator variables for reason a worker left his previous job (including: laid off or fired, end of program or temporary job, quit and first job); the omitted category is plant closing. X_i is the same vector of time-invarying characteristics specified above and ν_{igt} is an error term, clustered by individual since workers may be repeatedly sampled.[20] Here, the wages used to calculate wage changes are *all* observed at the new employer, immediately following a job separation. The layoff coefficient reveals whether the variance in wage changes at the new employer is smaller for laid-off workers, relative to workers who lost the previous job due to a plant closing.

The layoff strategy exploits exogenous variation in worker mobility (plant closings) to test the asymmetric learning model. The job-entry cohorts and occupations strategies, in contrast, test comparative statics from the model. The specification for the second-stage regression is a difference-in-differences strategy in both analyses, as shown in equation 11. The standard errors are again clustered by person in the occupations analysis and by entry year into the job held in $t-1$ in the job-entry cohorts analysis because this is the most

workers who enter firms in recessions are, on average, lower ability, the group fixed effects will take this into account.

[20] Results for all three analyses are robust to the inclusion of other controls from the first stage, such as tenure.

aggregated level of variation.[21]

$$\varepsilon^2_{igt} = \beta_0 + \beta'_1 I^{\text{group}}_{i,g} + \beta_2 I^{\text{stay}}_{it} + \beta'_3[I^{\text{stay}}_{it} * I^{\text{group}}_{i,g}] + \beta'_4 X_i + \nu_{igt} \tag{11}$$

Here, observations are not restricted to having the same employer in periods t and $t-1$. $I^{\text{stay}}_{i,t}$ is an indicator that equals 1 if the employer in period $t-1$ is the same as the employer in t. Note that even if a worker moves between periods, he is still categorized in the same group (either job-entry cohort or occupation). The wage change for a mover is the first wage at the *new* employer minus the last wage at the previous employer. The vector of coefficients on the interaction terms, β_3, test the predictions of the model: whether the difference in the variance in wage changes between groups among stayers is larger or smaller than the difference between groups among leavers.

Workers in different occupations or job-entry cohorts may differ systematically in ways that can affect the variance of wage changes. Similarly, stayers may differ from workers who choose to leave. Selection into groups might be of concern, but the benefit of the difference-in-differences strategy I use is that it controls for group fixed effects and a fixed effect for staying. My identification strategy relies on there not being differential selection in turnover across groups. Below I provide evidence that similar turnover is a reasonable assumption in this case.

Because the expectation of squared residuals is particularly sensitive to outliers, I also look at the inter-quartile ranges for the residuals. I estimate quantile regressions for the

[21] The same vector of controls, X_i, is included in both analyses and the occupations analysis additionally includes dummies for occupation in year t and interactions of this variable with occupation in year $t-1$. This allows me to control for the average spread of wage changes for each occupation combination.

residuals with the same controls as equations 10 and 11 for the 75^{th} and 25^{th} percentiles and take the difference. Standard errors are computed by bootstrapping with 5000 repetitions. In addition, I have estimated all squared-residual regressions excluding outliers.[22] I report these in the layoffs analysis, the only instance where results are sensitive to the treatment of outliers.

4 Results

4.1 Layoffs versus Plant Closings

In this section, I test proposition 2: Under asymmetric information, a group of endogenous movers has a lower variance in ability than a group of exogenous movers but under symmetric information there should be no difference. The empirical implementation is to observe the variance in wage changes at a new employer by reason for having left the previous employer, since proposition 1 shows that wage changes have lower variance when ability is lower variance. My identification comes from comparing laid-off or fired workers with workers who lost jobs due to plant closings. The first group are endogenous movers since firms have discretion in whom to let go. The second group are exogenous movers since it is unlikely that any individual worker is responsible for a plant closing.

I first confirm GK's main finding, that the wage change between jobs is more negative for laid-off workers than for workers who lost the previous job due to a plant closing. Table 1 shows the layoff coefficient in log wage and log wage change regressions for both the whole

[22] I define an observation to be an outlier if its residual (estimated in the first-stage regression) is greater than 1.6 or less than -1.6. Results are not sensitive to other cutoff points within a reasonable range. Results are similar when I Windsorize, rather than exclude outliers.

sample and then separately for workers displaced from a white collar job.[23] GK hypothesize that a layoff will be a more negative signal if layoff decisions are not subject to seniority or other union rules and assume that white collar jobs are more likely to satisfy this condition. I report OLS results and matching estimators. Workers displaced due to a plant closing differ from laid-off workers in observable characteristics; they are older when displaced, had higher tenure and are less well-educated. I therefore use a nearest-neighbor matching estimator (Abadie, Drukker, Herr and Imbens 2002), matching on education, race, displacement age and displacement tenure.[24]

In the NLSY, I find that laid-off workers do indeed experience larger wage losses upon entering a new job than workers displaced by a plant closing. The point estimate on the layoff coefficient is almost 0.03 log-point wage loss for the full sample or 0.042 when workers are matched. As in GK, the magnitude increases when the sample is restricted to white collar workers, here the effect is more than a 0.05 log-point wage loss. These coefficients are not statistically significant but the sample size for plant closings is quite small. The evidence presented here is broadly consistent with outside employers attaching negative stigma to laid-off workers, though it appears as though the effect is mainly driven by higher pre-displacement wages of laid-off workers.[25]

[23] Regressions also include the following controls, chosen to be as consistent to the methodology in GK as possible, as well as dummy variables for the other reasons for leaving the previous job: a quadratic in final tenure at the displaced job, education dummies, black and Hispanic dummies, geographic region and urban status, marital status, actual labor market experience (including at the displaced job), age at time of displacement, previous-occupation and previous-industry dummy variables, time in between losing previous job and starting current job and year-of-displacement dummies.

Note the sample size is smaller in these regressions because workers must have a valid final wage at the displaced job.

[24] Note for the matching estimators, only laid-off workers and those who lost a job due to a plant closing are included. Results are not sensitive to omitting any one of the variables used in matching.

[25] That the pre-displacement wages of laid off workers are larger than those in the plant closing sample is in contrast to both the theory and empirical results from GK. Krashinsky (2002) also finds this effect in the

To gain a sense of the distributions of the log wage-change residuals across different groups, I plot kernel densities for both the layoffs and plant closings samples, shown in figure 1. As can be seen, the density for workers who left their job due to a plant closing (the solid line) is more spread out than the density for laid-off workers (the dashed line). It is difficult to glean information about magnitudes or statistical significance from this picture, but the evidence is strongly suggestive that the plant closings sample has a higher variance in log wage changes than the layoffs sample.

Table 2 summarizes the main set of results for this section (estimating equation 10, above). Panel A reports the layoff coefficient for the squared residual regressions while panel B reports the layoff coefficient for the inter-quartile ranges, both relative to plant closings. The first set of columns includes the whole sample while the second restricts to workers whose previous job was in a white collar occupation. Since the effects of learning should be more prevalent early in an employment relationship, I run a separate analysis on low-tenure workers, restricting the sample to workers who have been at their new firm for fewer than 2 years.[26]

All coefficients in this table are negative, consistent with the asymmetric learning model. The first set of squared residual coefficients, estimated on the full sample, are small in magnitude but the matching estimator, excluding outliers, implies a decrease in variance of 0.03 for laid-off workers and is statistically significant at the 10% level. In the low tenure sample, the most relevant for employer learning, we see coefficients increase in magnitude and statistical significance. Excluding outliers, workers who were laid off, relative to those

NLSY and hypothesizes that it is due to differences in establishment size of the displacing firm: Laid-off workers lost jobs from larger firms and therefore had higher pre-displacement wages.

[26] That is, I exclude wage-change observations where tenure in year t is greater than or equal to 2 years.

who lost a job from a plant closing, have 0.063 lower variance, significant at the 5% level. Squared residual results for the white collar sample are similar. The inter-quartile range differences are also negative and statistically significant. In the full sample the range for laid-off workers is 0.068 smaller than for workers in the plant closing sample, statistically significant at the 1% level. Magnitude again increases in the low tenure sample to 0.138 and here it also increases for the white collar sample, consistent with a layoff being a more negative signal when employers are less restricted about whom they can lay off.

The magnitudes of these effects can be interpreted when compared to the sample variance and inter-quartile range of the log wage change residuals. For the low-tenure sample, these are 0.10 and 0.21, respectively. Therefore, both the variance and inter-quartile range of log wage change residuals fall by almost two-thirds the size of their totals in the layoff sample. This implies that the negative selection of laid-off workers, driven by asymmetric information, is quite large.

4.2 Job-Entry Cohorts

In this section, I test proposition 3: Under asymmetric information, the variance in wage changes of stayers responds *more* to different variances in ability than does the variance of wage changes for movers. The empirical implementation is to compare the variance in wage changes of two groups, a high variance ability group and a low variance ability group, across two states, moving and staying. My identification comes from labor market conditions at time of entry into a firm. I exploit the empirical phenomenon that workers who enter firms in better economies have higher variances in observable characteristics (and therefore, plausibly, higher variances in unobserved ability) than workers who enter firms in worse economies. One mechanism driving this could be the different pools of workers looking for jobs in recessions versus booms. During a recession, workers who quit are less likely than in boom-times to find a better job quickly, and so the threshold job quality for voluntary separation falls. As a result, a greater share of job-seekers are the unemployed or those leaving bad jobs. Thus, compared to a regular economy, the group of workers seeking jobs will have a lower-variance ability distribution.

Table 3 provides evidence that several characteristics of workers who start jobs in recessions are lower variance. Panel A shows squared residuals of characteristics by job-entry unemployment rate group.[27] Here, the groups represent unemployment rate quartiles.[28] Results are similar here (and those that follow in table 4) when the unemployment rate enters in linearly but I use the current specification to allow for more flexible functional form. The comparison between the highest and lowest unemployment rate groups is of primary interest since that yields the sharpest contrast. All jobs with a valid wage-change observation are included in the sample. Characteristics include year of birth, foreign born, number of siblings, highest grade completed, age-adjusted AFQT score and a log wage residual from the first wage observation at the employer.[29] The first row of coefficients shows the top quartile unemployment rate (the worst economies) relative to the bottom (best economies). As can be seen all coefficients are negative and, with the exception of number of siblings,

[27] Characteristics are regressed on unemployment rate fixed effects and residuals are obtained.

[28] The cutoffs for the quartiles are the following: <5.6, 5.6-6.2 6.8-7.2, >7.2. They are selected so that the job-entry cohorts have the same number of observations (not necessarily wage-change observations). In table B2, the number of jobs are not equal across groups because they reflect both the initial entry jobs and any movement across jobs.

[29] Log wage is residualized on a quadratic in age, marital status, and education, geographic region, urban status, black and Hispanic dummies.

statistically significant.

Of particular interest are highest grade completed, AFQT score and first log wage residual, all of which are negative and significant at the 1% or 5% level. Education is observable to both the employer and the econometrician. AFQT score is observable to the econometrician but probably not to the employer.[30] A first wage residual likely incorporates information available to the employer but not the econometrician. In all three of these cases, workers who enter firms in bad economies have a *lower* variance, a fact that is highly suggestive that they have a lower variance in unobserved ability as well. Comparing best and worst economies yields the sharpest contrast while the other rows show similar results, though smaller in magnitude, as would be expected.

Panel B of table 3 shows means of the same characteristics for each unemployment rate quartile. As can be seen, these groups of workers are not identical.[31] However, of the key three variables mentioned above, only highest grade completed is significant: workers who match to firms in worse economies have about a third of a year less schooling, on average. This is consistent with the above hypothesis that workers who enter firms in recessions are negatively selected. To the extent that groups differ, the difference-in-differences strategy is particularly useful: it allows each unemployment rate group to have a fixed effect, hopefully controlling for these and other differences between groups.

Table 4 summarizes the core set of results for this section, the squared residuals regressions and inter-quartile ranges. Equation 11, above, is estimated, where the groups are

[30] See Lange (2007) for a nice discussion of the unobservability of AFQT to employers.

[31] Year of birth is highly significant but this is largely mechanical. The structure of the NLSY implies that the better economies occurred mainly at the beginning of the sampling period while worse economies occurred later. Thus older workers are more likely to be working in better economies.

quartile of national unemployment rate; the omitted category is the lowest quartile. I report the coefficients for each unemployment rate group relative to the lowest quartile (the best economy), staying and their interactions. The first set of columns shows estimates for squared residuals while the second shows inter-quartile ranges. Here, for both the squared residuals and inter-quartile range, the difference-in-differences estimates for the worst economy (relative to the best) are negative and statistically significant at the 5% level. Wage changes are less spread out for workers who enter firms in a bad economy than in a good one and stay relative to this comparison among movers. The effect is also present in the low-tenure sample though its magnitude does not increase as we might have expected. Also note that the coefficient on staying is always negative and statistically significant at the 1% level. This is expected since there are many match-specific factors which remain constant when a worker stays at a firm (for example, compensating differentials) and vary when workers move firms.

The magnitude of the effect for the full sample is a decrease in the squared residual of 0.03 and a decrease in inter-quartile range of 0.046 when comparing the worst economy with the best. The coefficients on staying imply that stayers have a decreased variance of approximately 0.10 and a reduction in inter-quartile range of approximately 0.20. Therefore entering the firm in a recession reduces the variance in wage changes of stayers by 33% more than the base effect of staying and reduces the inter-quartile range by 23% more. This tells us that the variance in wage changes for stayers responds more to variance in ability than it does for movers, by a sizeable amount.

4.3 Occupations

In this section, I test proposition 4: Under asymmetric information, the variance in wage changes of stayers responds *less* to different levels of asymmetry than does the variance of wage changes for movers. The empirical implementation is to compare the variance in wage changes of two types of jobs, asymmetric jobs and symmetric jobs, across two states, moving and staying. My identification comes from occupations.

Specifically, I hypothesize that professionals working in service industries (hereafter prof-serv workers) have a more symmetric-learning environment whereas professionals in non-service industries (hereafter prof-non-serv workers) and managers (defined by the one-digit 1970 census occupation codes) work in more asymmetric-learning markets. Prof-serv workers (such as consultants, lawyers in law firms, accountants and health care givers) often interact with clients who can credibly spread information to outside employers and other potential clients. In fact, clients could be quite valuable to the worker in that a large number of consultants are in-housed by their clients.[32] In addition, the marketing literature emphasizes that long-term relationships are common in the professional services sector, in large part because clients can generate referrals and increase outside credentials (see for example Halinen 1997).

In contrast, it is unlikely that the outside market can glean as much about prof-non-serv workers (such as computer programmers, engineers, researchers and technicians) who do not interact with outsiders as often, or do not interact with the types of outsiders relevant to

[32] This can be seen, for example, in top-consultant.com (2007), a report on retention in the consulting industry, in which they conducted a survey of over 700 consultants in 140 firms and asked questions about turnover behavior.

their outside job-market options. For example, it is probably difficult for outside firms to discern the quality of an engineer working on a production-design team. Similarly in the case of managers, the incumbent firm has access to a large amount of information that outside firms would not. For example, the incumbent can measure number of widgets produced per hour, costs, profitability of the factory, returns on investments, etc. This information is not available to outside employers and in fact, is often kept quite secret. Although for public companies a signal of success (stock prices) exists, it is unlikely that any given manager has a large influence on this measure. Fee and Hadlock (2003) find that increases in stock value have no effect on manager turnover, (specifically, managers' being hired as managers in outside firms), although they do find an effect for CEO's.

The asymmetric information model predicts that lower ability workers are more likely to leave whereas the symmetric learning model predicts turnover is random. Therefore, in order to test the degree of asymmetric information in a market, I look at whether workers who leave jobs from that market appear negatively selected (when compared with stayers) than workers who leave jobs in other markets. Table 5 summarizes regressions of the form specified in equation 12.

$$char_{iot} = \alpha_0 + \alpha_1' I_{i,o}^{\text{occupation}} + \alpha_2 I_{i,t}^{\text{move}} + \alpha_3' [I_{i,o}^{\text{occupation}} * I_{i,t}^{\text{move}}] + \epsilon_{iot} \tag{12}$$

Here, $char$ is a characteristic of worker i, who was in occupation o in year $t-1$, but not necessarily in year t. $I_{i,t}^{\text{move}}$ is an indicator equalling 1 if the worker moved jobs between $t-1$ and t. $I_{i,o}^{\text{occupation}}$ is a vector of occupation dummies, primarily the one-digit occupation codes from the 1970 census with one exception: I disaggregate professionals into those working in service industries and those not in service industries.[33] Table 5 reports the main effect of moving, as well as interactions with the two key occupations, prof-non-serv workers and managers (relative to prof-serv workers), although indicators for all other occupations and their interactions with moving are also included.

Not surprisingly, I find that movers are negatively selected. They have lower AFQT scores, years of school, and tenure in $t-1$ (though surprisingly, they have larger log wage changes, relative to stayers, between periods t and $t-1$). In addition, the interaction terms are for the most part negative and significant. That is, the mover effects for workers who left jobs as managers or prof-non-serv workers are more negative than for workers who left prof-serv jobs. In addition, the final column of table 5 looks at the probability of being laid off or fired conditional on moving between periods. It reveals that managers and prof-non-serv workers are more likely to leave their jobs involuntarily than prof-serv workers. This evidence supports the notion that learning is more asymmetric for the employers of managers and prof-non-serv workers relative to the employers of prof-serv workers.[34]

Table 6 summarizes the core set of results for this section, the squared residuals regressions (from equation 11) and inter-quartile range estimates. I report the coefficients for managers and prof-non-serv (relative to prof-serv), staying and their interactions. The difference-in-differences estimates are positive and in most cases statistically significant. Squared residuals increase by approximately 0.10 for both prof-non-serv workers and managers who

[33] The other categories are manager, sales, clerical, craft, operative, transportation, laborer, farmer and services. The omitted category is professional service workers.

[34] One could also address this question by looking across occupations to see whether laid-off workers have lower test scores, education, tenure and wage changes (upon moving) than workers who lost jobs due to plant closings. The layoff effect is indeed more negative for prof-non-serv workers and managers, suggesting they are in more asymmetric markets (though the estimates are usually not statistically significant, probably due to small sample sizes once plant closings are disaggregated across occupations).

stay (relative to prof-serv workers), statistically significant at the 5% level in the full sample and at the 1% level in the low-tenure sample. The inter-quartile ranges are similar in magnitude and statistical significance for prof-non-serv workers but not for managers. Also note that as expected, the main effects for prof-non-serv and manager are negative (possibly driven by the prediction in the model that wage changes are less dispersed in asymmetric markets) and the coefficients on staying are negative and statistically significant at the 1% level. The magnitude of the interaction effects exactly offsets the negative main effect of staying in the squared residuals results and is half the size for the inter-quartile range for prof-non-serv workers. Thus these effects are even larger than in the previous section.

5 Alternative Explanations

Above I used three different identification strategies which provide evidence consistent with the asymmetric information model. However the link between variance in wage changes and employer learning is indirect. In this section, I discuss human capital investment, differential turnover and differences in match quality as potential drivers of the results.

5.1 Human Capital

Disparities in human capital investment could be driving all three results, though a different story is required for each case. If laid-off workers move to jobs where human capital is less important for productivity, relative to workers who lost jobs due to a plant closing, then I might find that their wage changes are less spread out, even in a perfect information world, because there are fewer differences in true productivity. In the job-entry cohort analysis, suppose human capital investment and ability are complements so that more able people should obtain higher levels of human capital (hypothesized for example by Gibbons and Waldman 1999). This implies that workers who enter firms in recessions would have a lower variance in human capital accumulation, because they are lower-variance in ability, resulting in a lower variance in wage changes. If the discrepancy in investment is for firm-specific human capital then we would see a lower variance among workers who entered firms in recessions for stayers but not for movers, the same result as that shown in table 4.[35] In the occupations analysis, one needs a more complicated story. For example, if general human capital is more important for prof-serv workers then we might see that their wage changes are more spread out relative to prof-non-serv workers and managers. However, one would also need that firm-specific human capital is more important for prof-non-serv workers and managers to get the result that stayers in these groups have larger variances in wage changes.

To examine whether human capital investments can explain my results, I would like to control for workers' investments. I do this in two ways. First, I control for direct measures of training reported in the NLSY. Each year, respondents were asked if they participated in a training program, though the definition of training program changes across years. I create a cumulative effect by summing across years then control for this effect in the first-stage regressions. Second, since the training measure is noisy and does not take into account all investment, in an alternative specification I control for a proxy: the workers ex-ante capacity

[35]That discrepancies in human capital acquisition exist across job-entry cohorts is plausible. Kahn (2007) finds that workers who graduate from college in bad economies earn substantially lower wages throughout their careers. This persistence in the wage effect is largely attributed to differences in human capital acquisition.

for investing. I assume that starting wage may be an indicator of ability. Thus workers who enter with a higher starting wage should invest in greater levels of human capital (under the complementarity model). Controlling for starting wage in a rich manner should partially account for this differential investment.

Workers in different groups do indeed differ in training levels and in starting wages: Laid-off workers have slightly less training and lower starting wages than workers who were displaced because of plant closings; workers who enter firms in recessions have less training and lower starting wages; prof-non-serv workers have more training that prof-serv workers and higher starting wages (though they do not differ from managers). However, appendix table B4 reports replications of all three analyses where the first-stage also controls for either training or for starting wage.[36] I find that the results do not change, suggesting that human capital is not driving them.

5.2 Differential Turnover

The job-entry cohorts and occupations strategies involve comparing movers and stayers across groups of workers. That workers who choose to leave their current job are not necessarily equivalent to those who stay is not a problem per se because I difference out a fixed effect for staying (as well as fixed effects for job-entry cohort or occupation). However, a problem would arise if the selection of movers and stayers varies across groups. This is less worrisome here because workers in my sample are young; I observe them from the start of their transition into the labor market. Young workers to move jobs often (see for example

[36] When start wage is included, it is also interacted with tenure year dummies and I control for start-year dummy variables to take into account economic conditions when first wages were set. Results do not differ substantially when either training or starting wage is also controlled for in the second stage regressions.

Topel and Ward (1992)). In fact, the average worker in my sample has had slightly more than 6 jobs. However, differential selection is plausible in some cases. For example, Bowlus (1995) finds that employer-employee matches are less successful (i.e., workers are more likely to turnover) when the employee starts work in a recession. This could be because they have fewer jobs to choose from. In addition, the propensity to leave one's job could vary across occupation.[37] To address this issue, I compare the means and variances of characteristics of movers and stayers across groups.

Appendix table B5 summarizes results for the job-entry cohort analysis, reporting both means and squared residuals for the highest and lowest unemployment-rate groups.[38] Statistical significance between the differences is noted in the far-right column. Here, in both groups, stayers have more education and higher AFQT scores than movers. They also have higher variances in education. However the far-right column shows that when the differences between movers and stayers are compared across job-entry cohorts, they are largely insignificant in both means and variances. This suggests that differential turnover patterns might not be a large confounding factor. On the other hand, in both unemployment rate groups, stayers have higher lagged tenure and a larger variance in lagged tenure than leavers but these differences are much larger for the high unemployment rate group. The tenure results could be driven by differences in match quality so I address this issue directly below. As a whole though, I would argue that differential turnover patterns are not driving the

[37] This could be the case, in part, because of asymmetric information. If outside employers know little, then a high-quality worker may be reluctant to leave since (s)he will not be valued as highly in the outside market. My model accounts for this issue with the parameter, r. Therefore, differences in turnover due to differences in asymmetry are probably not driving my results.

[38] Residuals are obtained by regressing each characteristic on unemployment rate group dummies, a dummy for staying and interactions

job-entry cohort results.

Appendix table B6 summarizes results for the occupations analysis. Here, the differences between movers and stayers are largely consistent across occupations (statistical significance across occupations is indicated in the columns between them). Among prof-serv workers, stayers do have a larger variance in years schooling compared to movers while prof-non-serv workers and managers have a lower variance, both comparisons significant at the 10% level. Since this is the only significant difference, I conclude that differential turnover is probably not driving my results.

5.3 Differences in Match Quality

Above, I discussed that workers who enter firms in different economies may differ in their match quality with the firm and thus their turnover propensities. To sign this bias, it is useful to think about the difference-in-differences estimator described above and shown again here.

$$dd_\sigma = (var_s^l - var_s^h) - (var_m^l - var_m^h)$$

I find that the estimate of dd_σ is negative and significant and would like to attribute this to asymmetric learning. However, suppose during recessions, certain types of jobs are closed off and these are jobs with higher variance in pay. Once the economy picks up and these jobs start hiring, workers in the high unemployment-rate group (the l category) will move with more frequency from low pay-variance jobs to high pay-variance jobs. This implies that the wage changes for movers will be high variance (because the period 2 wage is higher variant) while the wage changes for stayers will remain low variance, biasing the dd_σ estimate downward.

To address this, I can directly look to see whether the variance of wages for movers is high relative to the variance of pay upon entry to the initial firm. Appendix figure 1 show kernel densities for wage *levels* of workers who entered firms in the highest unemployment-rate quartile. The dashed line shows the distribution for starting wages while the solid line shows the distribution of the first wage at the new firm among movers. As can be seen, the distributions are almost identical. Therefore it is unlikely that differential rates of movement into high-variance in pay jobs is driving my results.

To look more generally at differences in match quality, I look at the reasons for leaving a job. There is evidence that in both the unemployment rate analysis and the occupations analysis, groups may differ in match quality. For example the high unemployment rate group is more likely to be laid off than the low unemployment rate group. Also managers and prof-non-serv workers are more likely to be laid off than prof-serv workers. Appendix table B7 reports estimates where the first-stage regressions also control for dummy variables for reason the worker left his job if he moved (or 0 if the worker stayed).[39] As can be seen, the results do not differ from the original specification, suggestions it is unlikely that differences in match quality are driving my results.

[39] Results do not change when reason is also controlled for in the second stage.

6 Conclusion

This paper seeks to establish whether asymmetric employer learning is prevalent in the labor market. I derive a model which embeds both symmetric and asymmetric learning and develop empirical predictions to test for the prevalence of asymmetric learning. I then test three separate predictions of the model using three distinct identification strategies. The first uses exogenous variation in turnover to test whether endogenous movers are negatively selected. The second analyzes comparative statics over variances in ability of groups, exploiting differences in job-entry cohorts. The third analyzes comparative statics over the degree of asymmetry in the market, using variation across occupations. I find strong support for the asymmetric learning model, even when subjected to a series of robustness checks.

These results are consistent with most of the previous empirical work in this area, though there have only been a few papers. Despite examining very different samples, GK, DeVaro and Waldman (2007), and Acemoglu and Pischke (1998) all find strong support for asymmetric information.[40] Schönberg (2007), the only other paper to use the NLSY, finds evidence consistent with asymmetric learning among college graduates but not among lower-educated workers. My results suggest that asymmetric information is important across education levels. For example, I find strong support for the asymmetric learning model among laid-off workers, a lower-educated group. The discrepancy is probably due to methodological differences and future work could further investigate the role of asymmetric information among low-educated workers.

The previous literature and the current paper, therefore, largely support the existence

[40] GK use the CPS Displaced Workers Supplement, DeVaro and Waldman (2004) use proprietary data from a single firm, and Acemoglu and Pischke (1998) provide evidence from German apprenticeship firms.

of asymmetric information and raise the question of how important it is. What proportion of information learned by incumbent employers is also learned by outside employers? The model presented in this paper is useful in that, if extended, it has the capacity to answer this question. It also provides methodology to study learning in a variety of settings without requiring particularly demanding data sets. Extensions could clarify thinking about the effects asymmetric information has on contracting, promotion policy, human capital investment and turnover behavior and perhaps policies that could alleviate inefficiencies.

A Theory Appendix

A.1 Deriving $w^*(\mu, s)$ and $v^*(s)$

As noted in the text, the incumbent firm maximizes the expected profit for each ability type, μ, and realization of s, (i.e., the probability that the worker stays times the profit for that worker), taking outside firms' behavior as given.

$$\begin{aligned} &\max_{w(\mu,s)} \left(\frac{w(\mu,s) - v^*(s) + \bar{\theta}}{2\bar{\theta}}\right)(\mu - w(\mu,s)) \\ \rightarrow \quad & w^*(\mu,s) = \frac{1}{2}(v^*(s) + \mu - \bar{\theta}) \end{aligned}$$

It is easy to show that the objective function is strictly quasi-concave. Therefore w^* is indeed a maximum and it is unique.

Outside firms set the wage offer equal to their expectation of worker ability conditional on s and the worker being willing to accept the wage offer. Bayes' rule yields the following equation.

$$v^*(s) = E(\mu|move) = \frac{\int_{-\infty}^{\infty} \mu * (1 - \Pr(\text{stay}|\mu, s)) * \Pr(\mu|s) d\mu}{1 - \Pr(stay|s)}$$

By plugging in for $\Pr(\text{stay}|\mu, s)$ and $w^*(\mu, s)$, given in equations 1 and 2 in the text, respectively, I solve for $v^*(s)$ as follows.

$$\begin{aligned} v^*(s) &= \frac{\int_{-\infty}^{\infty} \mu * (\frac{3\bar{\theta} - \mu + v^*(s)}{4\bar{\theta}}) * \Pr(\mu|s) d\mu}{\int_{-\infty}^{\infty} (\frac{3\bar{\theta} - \mu + v^*(s)}{4\bar{\theta}}) * \Pr(\mu|s) d\mu} \\ &= \frac{E(\mu|s)(3\bar{\theta} + v^*(s)) - E(\mu^2|s)}{3\bar{\theta} + v^*(s) - E(\mu|s)} \\ 0 &= (v^*(s))^2 + v^*(s)(3\bar{\theta} - 2E(\mu|s)) - E(\mu|s)3\bar{\theta} + E(\mu^2|s) \end{aligned}$$

Using the quadratic formula, I solve for the roots of this equation. Noting that the posterior distribution of μ, conditional on s, is normal with mean $\frac{mr+s}{1+r}$ and variance $\frac{r\sigma^2}{1+r}$, yields the expression for the solutions to $v^*(s)$.

$$\frac{mr + s}{1 + r} - \frac{3}{2}\bar{\theta} \pm \sqrt{\frac{9}{4}\bar{\theta}^2 - \frac{r\sigma^2}{1 + r}}$$

The model yields two pure-strategy equilibria, both of which are intuitive.[1] The right root implies high period 2 wages and high turnover while the left root yields low period 2 wages and low turnover. If many workers leave the incumbent firm then outside firms attribute high ability to them and offer a high wage, thus the incumbent must offer high wages to keep workers. In contrast, if only a few workers leave the firm, outside firms attribute a low ability to them and offer them a low wage, allowing the incumbent to offer a low wage. However, the left root is not stable, since if incumbent firms and workers expected a marginally higher wage, outside firms could earn a positive profit by offering it. Thus, I restrict attention to the right root for the rest of the analysis –though all results hold for the left root as well.

A.2 Solving for the first-period wage, w_0

Assuming no discounting, the incumbent firm's ex-ante expected profits, Π, are as follows.

$$\Pi = E[\mu] - w_0 + E[(\mu - w(\mu, s))|stay]$$

[1] Models of this form commonly yield multiple equilibria (see for example the following papers which focus on human capital acquisition under asymmetric information: Chang and Wang (1995), Prendergast (1992) and Acemoglu and Pischke (1998)).

Setting $\Pi = 0$ allows me to solve for w_0 as follows:

$$\begin{aligned}
w_0 &= m + \frac{\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}(\mu - w(\mu,s))\Pr(stay|\mu,s)\Pr(\mu|s)\Pr(s)d\mu ds}{\Pr(stay)} \\
&= m + \frac{1}{2}\left(\frac{\frac{r\sigma^2}{1+r}}{\frac{5}{2}\bar{\theta} - \sqrt{\frac{9}{4}\bar{\theta}^2 - \frac{r\sigma^2}{1+r}}} + \frac{5}{2}\bar{\theta} - \sqrt{\frac{9}{4}\bar{\theta}^2 - \frac{r\sigma^2}{1+r}}\right)
\end{aligned}$$

Note that w_0 equals ex-ante expected ability, m, plus a positive constant. In period 2, the incumbent makes positive profits due to its information rents and must therefore pay the worker above average productivity in period 1 to balance this. It is easy to show that w_0 is increasing in r, the degree to which information in the market is asymmetric. When outside firms have less information, the period 2 quasi rent of the incumbent firm is larger.

A.3 Variance in wage changes for stayers

In this subsection, I derive the variance of pay changes for workers who stay at the firm (i.e., workers who accept offer w^*), take its derivative with respect to σ^2 and show that the derivative is always positive. Starting from the following expression for Δw^{stay}, I derive the variance.

$$\begin{aligned}
\Delta w^{stay} &= \frac{1}{2}\left(\mu + \frac{mr+s}{1+r} - \frac{5}{2}\bar{\theta} + \sqrt{\frac{9}{4}\bar{\theta}^2 - \frac{r\sigma^2}{1+r}}\right) - w_0 \\
Var(\Delta w^{stay}) &= \frac{1}{4}\left(Var(\mu|stay) + \frac{1}{(1+r)^2}Var(s|stay) + 2\frac{1}{1+r}Cov(\mu,s|stay)\right)
\end{aligned}$$

Taking each piece at a time, I first solve for $Var(\mu|stay)$. This uses the fact that the variance of the posterior distribution of μ, $Var(\mu|s)$, is a constant, thanks to the normality assumptions. Using the law of iterated expectations, $Var(\mu|stay) = E[E(\mu^2|stay,s)|stay] - (E[E(\mu|stay,s)|stay])^2$. Therefore we have

$$\begin{aligned}
Var(\mu|stay) &= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\mu^2\frac{\Pr(stay|\mu,s)\Pr(\mu|s)\Pr(s)}{\Pr(stay|s)}d\mu ds - \left(\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\mu\frac{\Pr(stay|\mu,s)\Pr(\mu|s)\Pr(s)}{\Pr(stay|s)}d\mu ds\right)^2 \\
&= \frac{E(\mu^3) - E[E(\mu^2|s)E(\mu|s)] - Var(\mu|s)E(\mu)}{\frac{5}{2}\bar{\theta} - \sqrt{\frac{9}{4}\bar{\theta}^2 - \frac{r\sigma^2}{1+r}}} - \frac{(Var(\mu|s))^2}{(\frac{5}{2}\bar{\theta} - \sqrt{\frac{9}{4}\bar{\theta}^2 - \frac{r\sigma^2}{1+r}})^2} + Var(\mu) \\
&= \frac{E((\mu - E(\mu|s))^3)}{\frac{5}{2}\bar{\theta} - \sqrt{\frac{9}{4}\bar{\theta}^2 - \frac{r\sigma^2}{1+r}}} + \sigma^2 - \frac{(\frac{r\sigma^2}{(1+r)})^2}{(\frac{5}{2}\bar{\theta} - \sqrt{\frac{9}{4}\bar{\theta}^2 - \frac{r\sigma^2}{1+r}})^2}
\end{aligned}$$

But the $E((\mu - E(\mu|s))^3) = E[E((\mu - E(\mu|s))^3|s)]$ by the law of iterated expectations. The latter expression is the skew of the posterior distribution. Since the posterior is normally distributed, its skew is 0. Therefore equation 1 gives the variance of μ conditional on staying.

$$Var(\mu|stay) = \sigma^2 - \frac{(\frac{r\sigma^2}{(1+r)})^2}{(\frac{5}{2}\bar{\theta} - \sqrt{\frac{9}{4}\bar{\theta}^2 - \frac{r\sigma^2}{1+r}})^2} \tag{1}$$

I now derive the variance of s conditional on staying.

$$\begin{aligned}
Var(s|stay) &= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}s^2\frac{\Pr(stay|\mu,s)\Pr(\mu|s)\Pr(s)}{\Pr(stay|s)}d\mu ds - \left(\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}s\frac{\Pr(stay|\mu,s)\Pr(\mu|s)\Pr(s)}{\Pr(stay|s)}d\mu ds\right)^2 \\
&= \frac{\int_{-\infty}^{\infty}s^2(\frac{5}{2}\bar{\theta} - \sqrt{\frac{9}{4}\bar{\theta}^2 - \frac{r\sigma^2}{1+r}})\Pr(s)ds}{\frac{5}{2}\bar{\theta} - \sqrt{\frac{9}{4}\bar{\theta}^2 - \frac{r\sigma^2}{1+r}}} - \left(\frac{\int_{-\infty}^{\infty}s(\frac{5}{2}\bar{\theta} - \sqrt{\frac{9}{4}\bar{\theta}^2 - \frac{r\sigma^2}{1+r}})\Pr(s)ds}{\frac{5}{2}\bar{\theta} - \sqrt{\frac{9}{4}\bar{\theta}^2 - \frac{r\sigma^2}{1+r}}}\right)^2 \\
&= E(s^2) - (E(s))^2
\end{aligned}$$

The conditional variance of s equals the unconditional variance of s. Because both outside employers and incumbent employers see s, the incumbent will set wages so that, conditional on s, the worker is indifferent between staying and leaving. Since $s = \mu + \epsilon$ and $\mu \perp \epsilon$, the variance is just the sum of these variances, shown in equation 2.

$$Var(s|stay) = (1+r)\sigma^2 \tag{2}$$

Lastly, I solve for the covariance of s and μ conditional on staying.

$$\begin{aligned} Cov(\mu, s|stay) &= E(\mu * s|stay) - E(\mu|stay)E(s|stay) \\ &= \frac{Var(\mu|s)E(s)}{\frac{5}{2}\bar{\theta} - \sqrt{\frac{9}{4}\bar{\theta}^2 - \sigma^2}} + E[E(\mu|s) * s] - (\frac{Var(\mu|s)E(s)}{\frac{5}{2}\bar{\theta} - \sqrt{\frac{9}{4}\bar{\theta}^2 - \sigma^2}} + E(\mu)E(s)) \\ &= E[E(\mu|s) * s] - E(\mu)E(s) \\ &= \sigma^2 \end{aligned} \tag{3}$$

Plugging in equations 1-3 into the above formula for the variance in wage changes conditional on staying at the firm yields the following expression, replicated from equation 7 in the text.

$$Var(\Delta w^{stay}) = \frac{1}{4}(\frac{4+r}{1+r}\sigma^2 - \frac{(\frac{r\sigma^2}{(1+r)})^2}{(\frac{5}{2}\bar{\theta} - \sqrt{\frac{9}{4}\bar{\theta}^2 - \frac{r\sigma^2}{1+r}})^2})$$

Next, we need to sign the derivative with respect to σ^2which is shown below.

$$\frac{\partial Var(\Delta w^{stay})}{\partial \sigma^2} = \frac{1}{1+r} + \frac{1}{4}\frac{r}{1+r}(1 - \frac{2\frac{r\sigma^2}{1+r}}{(\frac{5}{2}\bar{\theta} - \sqrt{\frac{9}{4}\bar{\theta}^2 - \frac{r\sigma^2}{1+r}})^2} + \frac{(\frac{r\sigma^2}{1+r})^2}{\sqrt{\frac{9}{4}\bar{\theta}^2 - \frac{r\sigma^2}{1+r}}(\frac{5}{2}\bar{\theta} - \sqrt{\frac{9}{4}\bar{\theta}^2 - \frac{r\sigma^2}{1+r}})^3}) \tag{4}$$

A sufficient condition for $\frac{\partial Var(\Delta w^{stay})}{\partial \sigma^2}$ to be positive is condition 1. It can be shown that as long as $\bar{\theta}$ is sufficiently large, (i.e., $\frac{\bar{\theta}^2}{3} \geq \sigma^2$), this condition always holds.

Condition 1 $0 < 1 - \frac{2\frac{r\sigma^2}{1+r}}{(\frac{5}{2}\bar{\theta} - \sqrt{\frac{9}{4}\bar{\theta}^2 - \frac{r\sigma^2}{1+r}})^2} + \frac{(\frac{r\sigma^2}{1+r})^2}{\sqrt{\frac{9}{4}\bar{\theta}^2 - \frac{r\sigma^2}{1+r}}(\frac{5}{2}\bar{\theta} - \sqrt{\frac{9}{4}\bar{\theta}^2 - \frac{r\sigma^2}{1+r}})^3}$

A.4 Variance in wage changes for movers

I first derive the variance in ability conditional on moving. This is solved in a similar manner to the variance of μ conditional on staying. Here $\Pr(move|\mu, s) = 1 - \Pr(stay|\mu, s) = -\mu + \frac{mr+s}{1+r} + \frac{3}{2}\bar{\theta} + \sqrt{\frac{9}{4}\bar{\theta}^2 - \frac{r\sigma^2}{1+r}}$

$$\begin{aligned} Var(\mu|move) &= E[E(\mu^2|move, s)|move] - (E[E(\mu|move, s)|move])^2 \\ & \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} \mu^2 \frac{(1 - \Pr(stay|\mu, s))\Pr(\mu|s)\Pr(s)}{1 - \Pr(stay)} d\mu ds - (\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} \mu \frac{(1 - \Pr(stay|\mu, s))\Pr(\mu|s)\Pr(s)}{1 - \Pr(stay)} d\mu \\ &= \frac{-E((\mu - E(\mu|s))^3)}{\frac{3}{2}\bar{\theta} + \sqrt{\frac{9}{4}\bar{\theta}^2 - \frac{r\sigma^2}{1+r}}} + \sigma^2 - \frac{(\frac{r\sigma^2}{(1+r)})^2}{(\frac{3}{2}\bar{\theta} + \sqrt{\frac{9}{4}\bar{\theta}^2 - \frac{r\sigma^2}{1+r}})^2} \end{aligned}$$

But here, again, since the skew of the posterior distribution of μ is 0, we have the following expression. This is obviously less than σ^2 since a positive value is subtracted from σ^2.

$$Var(\mu|move) = \sigma^2 - \frac{(\frac{r\sigma^2}{(1+r)})^2}{(\frac{3}{2}\bar{\theta} + \sqrt{\frac{9}{4}\bar{\theta}^2 - \frac{r\sigma^2}{1+r}})^2}$$

I now solve for the variance in wage changes among movers. Starting from the following expression for Δw^{move}, I derive the variance.

$$\begin{aligned}
\Delta w^{move} &= \frac{mr+s}{1+r} - \frac{3}{2}\bar{\theta} + \sqrt{\frac{9}{4}\bar{\theta}^2 - \frac{r\sigma^2}{1+r}} - w_0 \\
Var(\Delta w^{move}) &= \frac{1}{(1+r)^2} Var(s|move)
\end{aligned}$$

But above I showed that the variance of s conditional on staying equals the unconditional variance of s. Therefore the variance of s conditional on moving also equals the unconditional variance (since workers can only either stay or move). Since $var(s) = (1+r)\sigma^2$, we get the following expression:

$$Var(\Delta w^{move}) = \frac{\sigma^2}{1+r}$$

Also note that $\frac{\partial Var(\Delta w^{move})}{\partial \sigma^2} = \frac{1}{1+r}$.

A.5 Comparing $\frac{\partial Var(\Delta w^{stay})}{\partial \sigma^2}$ and $\frac{\partial Var(\Delta w^{move})}{\partial \sigma^2}$

In this section, I prove proposition 3 in the paper by showing that $\frac{\partial Var(\Delta w^{stay})}{\partial \sigma^2} > \frac{\partial Var(\Delta w^{move})}{\partial \sigma^2}$. To do this, I subtract $\frac{1}{1+r}$ from equation 4, yielding the following expression. Thanks to condition 1, above, this is always positive.

$$\frac{1}{4}\frac{r}{1+r}\left(1 - \frac{2\frac{r\sigma^2}{1+r}}{(\frac{5}{2}\bar{\theta} - \sqrt{\frac{9}{4}\bar{\theta}^2 - \sigma^2})^2} + \frac{(\frac{r\sigma^2}{1+r})^2}{\sqrt{\frac{9}{4}\bar{\theta}^2 - \sigma^2}(\frac{5}{2}\bar{\theta} - \sqrt{\frac{9}{4}\bar{\theta}^2 - \sigma^2})^3}\right) > 0$$

A.6 Degree of asymmetry

In this section, I first show that the derivatives of the variance in wage changes with respect to r, the degree of asymmetry are negative for both movers and stayers. Expressions for $\frac{\partial Var(\Delta w^{stay})}{\partial r}$ and $\frac{\partial Var(\Delta w^{move})}{\partial r}$ are as follows.

$$\begin{aligned}
\frac{\partial Var(\Delta w^{stay})}{\partial r} &= \frac{1}{4}\frac{\sigma^2}{(1+r)^2}\left(-3 - \frac{2\frac{r\sigma^2}{1+r}}{(\frac{5}{2}\bar{\theta} - \sqrt{\frac{9}{4}\bar{\theta}^2 - \sigma^2})^2} + \frac{(\frac{r\sigma^2}{1+r})^2}{\sqrt{\frac{9}{4}\bar{\theta}^2 - \sigma^2}(\frac{5}{2}\bar{\theta} - \sqrt{\frac{9}{4}\bar{\theta}^2 - \sigma^2})^3}\right) \\
\frac{\partial Var(\Delta w^{move})}{\partial r} &= \frac{-\sigma^2}{(1+r)^2}
\end{aligned}$$

The second, $\frac{\partial Var(\Delta w^{move})}{\partial r}$, is clearly negative since both σ^2 and $(1+r)^2$ are positive. In the first, a sufficient condition for $\frac{\partial Var(\Delta w^{stay})}{\partial r}$ to be less than 0 is condition 2. It can be shown that this always holds.

Condition 2 $\frac{(\frac{r\sigma^2}{1+r})^2}{\sqrt{\frac{9}{4}\bar{\theta}^2-\sigma^2}(\frac{5}{2}\bar{\theta}-\sqrt{\frac{9}{4}\bar{\theta}^2-\sigma^2})^3} < 3$

I now prove proposition 4 in the text, by showing that $\frac{\partial Var(\Delta w^{stay})}{\partial r} > \frac{\partial Var(\Delta w^{move})}{\partial r}$. This will be true if and only if the following expression holds.

$$\begin{aligned}
\frac{1}{4}\frac{\sigma^2}{(1+r)^2}\left(-3+4 - \frac{2\frac{r\sigma^2}{1+r}}{(\frac{5}{2}\bar{\theta} - \sqrt{\frac{9}{4}\bar{\theta}^2 - \sigma^2})^2} + \frac{(\frac{r\sigma^2}{1+r})^2}{\sqrt{\frac{9}{4}\bar{\theta}^2 - \sigma^2}(\frac{5}{2}\bar{\theta} - \sqrt{\frac{9}{4}\bar{\theta}^2 - \sigma^2})^3}\right) &> 0 \\
iff\ \frac{1}{4}\frac{\sigma^2}{(1+r)^2}\left(1 - \frac{2\frac{r\sigma^2}{1+r}}{(\frac{5}{2}\bar{\theta} - \sqrt{\frac{9}{4}\bar{\theta}^2 - \sigma^2})^2} + \frac{(\frac{r\sigma^2}{1+r})^2}{\sqrt{\frac{9}{4}\bar{\theta}^2 - \sigma^2}(\frac{5}{2}\bar{\theta} - \sqrt{\frac{9}{4}\bar{\theta}^2 - \sigma^2})^3}\right) &> 0
\end{aligned}$$

But this will be true as long as condition 1, above, holds.

B Data Appendix

The data set used in this paper is the 1979 National Longitudinal Survey of Youth (NLSY79) from 1979-2000. Starting in 1979, 12,686 youths between the ages of 14 and 21 were interviewed annually until 1994, then biannually thereafter. In this paper, the sample is restricted to the male cross-section sample (N=3,003), omitting women and the oversamples of blacks, Hispanics, military and poor whites. These groups are excluded because it is important to isolate workers with strong attachment to the labor market. In addition to the restrictions described in the text, I exclude jobs during which the worker was enrolled in school at any point. All wage observations must have valid occupation and industry codes and all jobs must have a valid observation for the starting wage at that job, since employer learning will be most important early in a worker's tenure.

The NLSY is particularly well-suited to this study because it contains a wealth of information on jobs and job changes. In each year, respondents can list up to five employers they had that year and these employer-employee matches can be tracked over time, allowing me to construct a detailed work history with start and stop dates and annual wage measures. I construct a sample where an observation is a person-employer match, creating a unique job ID within each person so that jobs are ordered chronologically. This sample is then reshaped so that each person-employer has possibly several wage-change observations. Appendix table A1 summarizes creation of the main variables used.

In the layoffs analysis, I exclude wage-change observations where the worker changed employers between wage observations. Thus, to be included in the analysis, a worker-employer match must have at least two consecutive wage observations and the worker must have a valid reason for having left the previous employer. This excludes approximately half the jobs in the sample with a reason for having left the previous job where either wage data are missing or the worker only stayed for one period. While this is a large number of jobs, selection out of the sample does not appear to be systematic across reasons for leaving the previous job.

The job-entry cohorts and occupations analyses include all wage-change observations meeting the above criteria (allowing workers to move between jobs). The sample sizes differ slightly because in the occupations analysis, observations must have valid occupation and industry codes in both years of the wage change (t and $t-1$), not just in t.

References

[1] Abadie, A., D. Drukker, J. Herr and G. Imbens (2004): "Implementing Matching Estimators for Average Treatment Effects in Stata," *The STATA Journal*, vol 4(3), pp. 290-311.

[2] Acemoglu, D. and J.-S. Pischke (1998): "Why Do Firms Train: Theory and Evidence," *Quarterly Journal of Economics*, 113:79-119.

[3] Altonji, J.G. and C.R. Pierret (2001): "Employer Learning and Statistical Discrimination," *Quarterly Journal of Economics*, 113:79-119.

[4] Bernhardt, D. (1995), "Strategic Promotion and Compensation," *Review of Economic Studies*, 62, pp. 315-339.

[5] Bowlus, A. (1995): "Matching Workers and Jobs: Cyclical Fluctuations in Match Quality," *Journal of Labor Economics*, 13:335-350.

[6] Chang, C. and Y. Wang (1995): "A Framework for Understanding Differences in Labor Turnover and Human Capital Investments," *Journal of Economic Behavior and Organization*, XXVIII: 91-105.

[7] Chang, C. and Y. Wang (1996), "Human Capital Investment Under Asymmetric Information: The Pigovian Conjecture Revisted," *Journal of Labor Economics*, 14, pp. 555-570.

[8] DeVaro, J. and M. Waldman (2007): "The Signaling Role of Promotions: Further Theory and Empirical Evidence," Cornell University, mimeo.

[9] Farber, H.S. (1999): "Mobility and Stability: The Dynamics of Job Change in Labor Markets," in O. Ashenfelter and D. Card, eds., *Handbook of Labor Economics*, vol. 3, North-Holland, pp. 2439-2483.

[10] Farber, H.S. and R. Gibbons (1996): "Learning and Wage Dynamics," *Quarterly Journal of Economics*, 111:1007-1047.

[11] Fee, C.E. and C.J. Hadlock (2003): "Raids, Rewards, and Reputations in the Market for Managerial Talent," *The Review of Financial Studies*, 16(4): 1315-1357.

[12] Gibbons, R. and L.F. Katz (1991): "Layoffs and Lemons," *Journal of Labor Economics*, 9:351-380.

[13] Gibbons, R. and M. Waldman (1999): "A Theory of Wage and Promotion Dynamics inside Firms," *Quarterly Journal of Economics*, 114:1321-1358.

[14] Greenwald, B.C. (1986): "Adverse Selection in the Labor Market," *Review of Economic Studies*, 53:325-347.

[15] Halinen, A. (1997): "Relationship Marketing in Professional Services." Routledge: London.

[16] Kahn, L.B. (2007): "The Long-Term Labor Market Consequences of Graduating from College in a Bad Economy," Harvard University, mimeo.

[17] Katz, E. and A. Ziderman (1990), "Investment in General Training: The Role of Information and Labour Mobility," *Economic Journal*, 100, pp. 1147-1158.

[18] Krashinsky, H. (2002). "Evidence on Adverse Selection and Establishment Size in Labor Markets." *Industrial and Labor Relations Review*, 56(1): 84-96.

[19] Lange, F. (2007): "The Speed of Employer Learning." *Journal of Labor Economics*, 25: 1-35.

[20] Milgrom, P. and S. Oster (1987): "Job Discrimination, Market Forces, and the Invisibility Hypothesis," *Quarterly Journal of Economics*, 102, pp. 453-476.

[21] Pinkston, J.C. (2005): "A Model of Asymmetric Employer Learning with Testable Implications," BLS Working Paper 390.

[22] Prendergast, C. (1992): "Career Development and Specific Human Capital Collection," *Journal of the Japanese and International Economics*, VI: 207-227.

[23] top-consultant.com (2007), "Retention Report 2007: A Key Challenge for the Management Consultancy Sector."

[24] Topel, R. and M. Ward (1992): "Job Mobility and the Careers of Young Men," *Quarterly Journal of Economics*, 107: 441-479.

[25] Schönberg, U. (2007): "Testing for Asymmetric Employer Learning" *Journal of Labor Economics,* 25, pp. 651-692.

[26] Waldman, M. (1984): "Job Assignment, Signalling and Efficiency," *RAND Journal of Economics*, 15:255-267.

[27] Waldman, M. (1990): "Up-or-Out Contracts: A Signaling Perspective," *Journal of Labor Economics*, 8, pp. 230-250.

[28] von Wachter, T. and S. Bender (2006): "In the Right Place at the Wrong Time - The Role of Firms and Luck in Young Workers' Careers," *American Economic Review* 96: 1679-1705.

[29] Zabojnik, J. and D. Bernhardt (2001): "Corporate Tournaments, Human Capital Acquisition, and the Firm Size-Wage Relation," *Review of Economic Studies*, 68, pp. 693-716.

Figure 1:

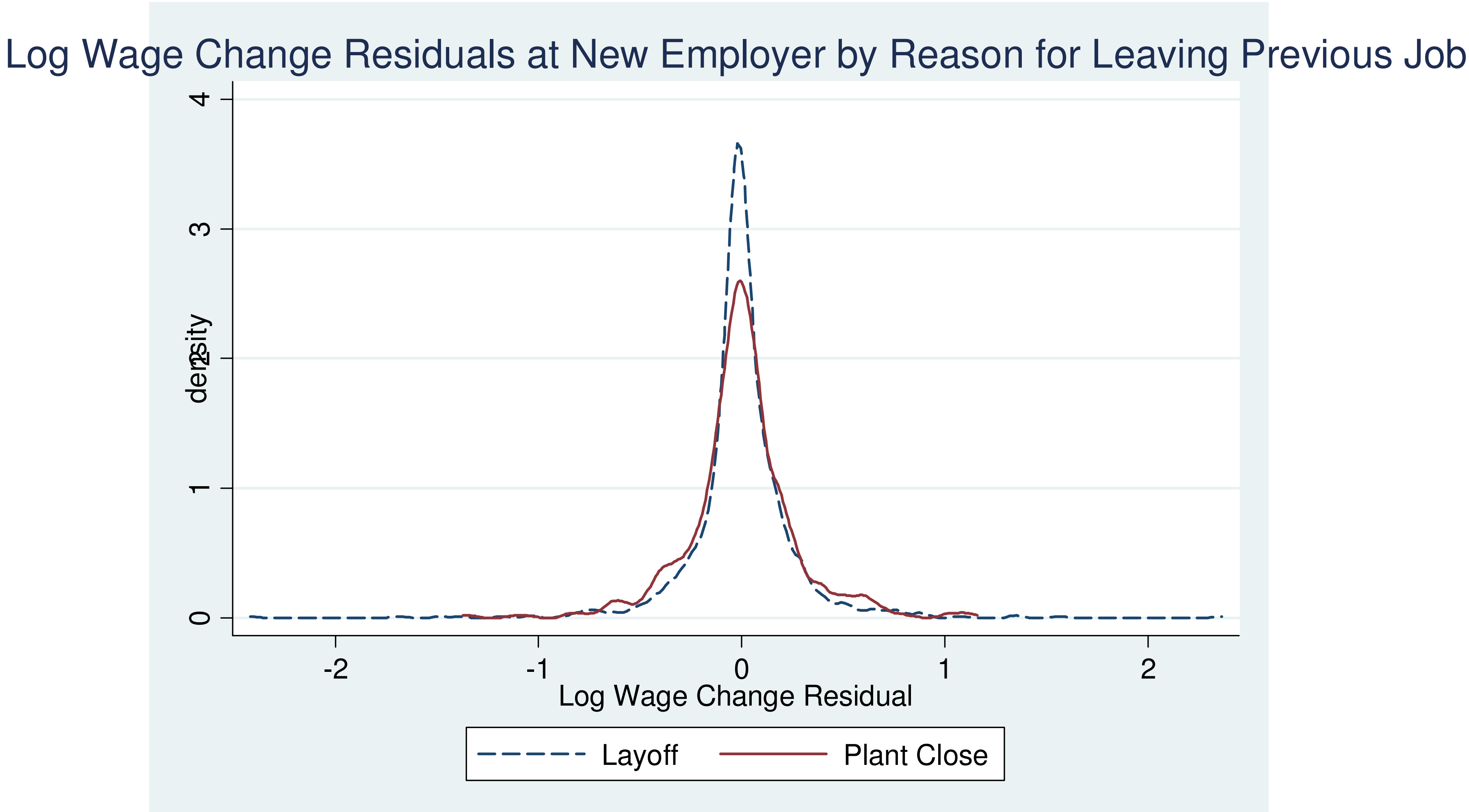

Log Wage Change Residuals at New Employer by Reason for Leaving Previous Job
density
0
1
2
3
4
-2
-1
0
1
2
Log Wage Change Residual
Layoff
Plant Close

Table 1 GK Replication: Earnings Equations for Displaced Workers, Coefficients on Layoff Dummy[1]			
	Dependent Variable		
	Wage Change	**Predisplacement**	**Postdisplacement**
A: Whole Sample (n=4341)			
OLS	-0.027	0.035	0.009
	[0.036]	[0.034]	[0.035]
Matching[2]	-0.042	0.070	0.028
	[0.031]	[0.033]*	[0.032]
B. White Collar[3] (n=1346)			
OLS	-0.054	0.054	-0.008
	[0.064]	[0.066]	[0.066]
Matching[2]	-0.056	0.055	-0.001
	[0.060]	[0.062]	[0.064]

Robust standard errors in parentheses, clustered by person.

+ significant at 10%; * significant at 5%; ** significant at 1%

Regressions only includes wage changes where the individual stays with the same employer.

1. Regressions also include dummy variables for the other reasons for having left the previous job (quit, job ended, where the omitted category is plant closing), as well as the following control variables: a quadratic in final tenure at the displaced job, education dummies, blakc and Hispanic dummies, geographic region and urban status, marital status, actual labor market experience (including at the displaced job), age at time of displacement, displaced-occupation and displaced-industry dummies, time in between losing previous job and starting current job and year-of-displacement dummies.

2. Matching estimator based on nearest-neighbor simple matching (Abadie et al). Estimation restricted to layoffs and plant closings, matched based on education, race, displacement age and displacement tenure

3. Regression restricted to workers displaced from white collar occupations (i.e., professionals/tech workers, managers, clerical and sales)

Includes the cross-section, non-military male sample of the NLSY from 1979-2000. Only post-transition, full time, non self employed, non enrolled wage observations are included. Transition year is defined by the beginning of the first two-year spell primarily working. Individual must have a valid starting wage at the current employer.

Table 2: Spread of Log Wage Change Residuals[1] at New Employer by Reason for Leaving Previous Employer

A: Squared Residuals, Coefficients on Layoff Dummy[2]

	All		**White Collar[4]**	
	All	**No Outliers[6]**	**All**	**No Outliers[6]**
	Whole Sample (n=14370, white collar n=3318)			
OLS	-0.009	-0.017	-0.013	-0.024
	[0.014]	[0.012]	[0.022]	[0.017]
Matching[3]	-0.022	-0.029	-0.011	-0.029
	[0.020]	[0.016]+	[0.031]	[0.021]
	Low Tenure[5] (n=4843, white collar n=1117)			
OLS	-0.053	-0.063	-0.046	-0.060
	[0.029]+	[0.028]*	[0.038]	[0.034]+
Matching[3]	-0.039	-0.049	-0.03	-0.048
	[0.029]	[0.024]*	[0.043]	[0.033]

B: Inter-Quartile Range of Residuals, Coefficient on Layoff Dummy[7]

	All	**White Collar[4]**
Whole Sample	-0.068	-0.087
	[0.021]**	[0.048]+
Low Tenure[5]	-0.138	-0.172
	[0.057]*	[0.117]

+ significant at 10%; * significant at 5%; ** significant at 1%

In panel A: Robust standard errors in brackets, clustered by person.

In panel B: standard errors computed by bootstrapping with 5000 repetitions.

Regressions only includes wage changes where the individual stays with the same employer.

1. Residuals obtained from a regression of log wage change on the following variables: Reason for leaving previous employer, a quadratic in age, dummy variables for year tenure, dummy variables for previous-period tenure, change in squared tenure, final tenure with previous employer, education dummies, geographic region and urbanicity dummies, marital status, actual labor market experience, year effects, black and hispanic dummies, industry and occupation dummies, dummies for having changed occupation or industry and time between employers.

2. Second-stage regression also includes dummy variables for other categories of reason for leaving previous job (quit, job end and first job) as well as race, Hispanic and education dummy variables

3. Matching estimator based on nearest-neighbor simple matching (Abadie et al). Estimation restricted to layoffs and plant closings, matched based on education, race, displacement age and displacement tenure

4. Only includes workers who previously worked in a white collar job

5. Restricted to observations with tenure less than two years (in second wage observation).

6. Restricted to residual values between 1.6 and -1.6.

7. Estimates obtained by differencing the coefficients from quantile regressions (75th %ile and 25th %ile) and bootstrapping with 5000 repetitions to obtain standard errors. Quantile regressions include controls specified in note 2.

Includes the cross-section, non-military male sample of the NLSY from 1979-2000. Only post-transition, full time, non self employed, non enrolled wage observations are included. Transition year is defined by the beginning of the first two-year spell primarily working. Individual must have a valid starting wage at the current employer.

Table 3: Characteristics by National Job-Entry Cohort[1]

	Year of Birth	Foreign Born	Number of Siblings	Highest Grade	AFQT	First Wage Residual[3]
A: Squared Residuals[2] (relative to lowest quartile)						
75-100%ile UE Rate	-0.439	-0.011	-0.257	-1.476	-0.085	-0.053
	[0.184]*	[0.004]*	[0.388]	[0.292]**	[0.035]*	[0.018]**
50-75 %ile UE Rate	-0.363	-0.011	-0.287	-0.843	-0.05	-0.044
	[0.235]	[0.007]	[0.328]	[0.304]**	[0.025]+	[0.019]*
25-50%ile UE Rate	-0.303	-0.017	-0.656	-0.795	-0.043	0.006
	[0.291]	[0.004]**	[0.348]+	[0.463]+	[0.028]	[0.021]
B: Means (relative to lowest quartile)						
75-100%ile UE Rate	-0.525	-0.012	-0.04	-0.325	-0.031	-0.028
	[0.170]**	[0.005]*	[0.064]	[0.094]**	[0.026]	[0.020]
50-75 %ile UE Rate	-0.398	-0.012	-0.031	-0.12	-0.032	-0.014
	[0.199]+	[0.008]	[0.068]	[0.098]	[0.030]	[0.018]
25-50%ile UE Rate	-0.408	-0.019	-0.056	-0.227	-0.027	0.030
	[0.287]	[0.005]**	[0.049]	[0.144]	[0.031]	[0.020]
Observations	12366	12366	12355	12366	11958	12366

Robust standard errors in brackets clustered by job-entry year

+ significant at 10%; * significant at 5%; ** significant at 1%

1. Job-Entry Cohort is defined as the national unemployment rate in the year the worker started his job. The cutoffs for the quartiles are the following: <5.6, 5.6-6.2, 6.8-7.2, >7.5.
2. Characteristics are regressed on unemployment rate fixed effects and residuals are obtained
3. The first log wage at the employer is residualized on the following variables: education dummies, geographic region and urban status dummies, a quadratic in age, black and hispanic dummies.

Sample includes the cross-section, non-military male sample of the NLSY from 1979-2000 .
All jobs with at least one wage-change observation meeting the following criteria are included.
Post-transition, full time, non self employed, non enrolled work.

Table 4: Spread of Log Wage Change Residuals[1] by Job-Entry UE Rate				
	Squared Residuals[2]		**Inter-Quartile Range[3]**	
	All	**Low Tenure[4]**	**All**	**Low Tenure[4]**
Unemployment rate[5] (relative to lowest quartile)				
Stay*75-100%ile	-0.030	-0.022	-0.046	-0.035
	[0.014]*	[0.008]*	[0.018]*	[0.022]
Stay*50-75%ile	-0.019	-0.02	-0.011	0.008
	[0.015]	[0.014]	[0.019]	[0.023]
Stay*25-50%ile	0.00013	0.013	-0.002	0.006
	[0.014]	[0.013]	[0.018]	[0.022]
Stay at Employer	-0.098	-0.096	-0.224	-0.194
	[0.010]**	[0.007]**	[0.014]**	[0.017]**
75-100%ile UE Rate	0.012	0.014	0.053	0.050
	[0.012]	[0.013]	[0.017]**	[0.017]**
50-75 %ile UE Rate	0.019	0.018	0.014	0.018
	[0.016]	[0.018]	[0.018]	[0.018]
25-50%ile UE Rate	0.013	0.016	0.015	0.013
	[0.012]	[0.013]	[0.017]	[0.017]
Observations	29739	16257	29739	16257
R-squared	0.01	0.01		

Standard errors in squared residuals panel clustered by person.

Standard errors in inter-quartile range panel obtained by bootstrapping with 5000 repetitions.

+ significant at 10%; * significant at 5%; ** significant at 1%

1. Log wage changes regressed on the following and squared residuals are obtained: Job-entry quartile dummies, an indicator for staying and all interactions, a quadratic in age, dummy variables for year tenure, dummy variables for previous-period tenure, change in squared tenure, final tenure with previous employer if moves (otherwise 0), education dummies, geographic region and urban status dummies, marital status, actual labor market experience, year effects, black and hispanic dummies, current industry and occupation dummies, and dummies for having changed industry or occupation.

2. Regressions also include controls for race and education.

3. Estimates obtained by differencing the coefficients from quantile regressions (75th %ile and 25th %ile) and bootstrapping with 5000 repetitions to obtain standard errors. Quantile regressions include controls specified in note 2.

4. Restricted to observations with tenure less than 2 years (in second wage observation).

5. Refers to the national unemployment rate in the year the individual started working for the employer in the t-1 period of the wage-change observation. The cutoffs for quartiles are: <5.6, 5.6-6.2, 6.8-7.2, >7.2.

Includes the cross-section, non-military male sample of the NLSY from 1979-2000. Only post-transition, full time, non self employed, non enrolled wage observations are included. Transition year is defined by the beginning of the first two-year spell primarily working. Individual must have a valid starting wage at the current employer.

Table 5: Characteristics of Movers by Occupation									
	AFQT		Highest Grade Completed		Previous Tenure		Log Wage Change		Pr(Layoff/Fired cond'l on move)[2]
Move	-0.159	-0.016	-0.276	0.034	-301.980	-37.588	0.048	0.113	--
	[0.019]**	[0.056]	[0.041]**	[0.217]	[6.939]**	[10.546]**	[0.005]**	[0.024]**	
Occupation (rel to prof-service)									
Prof Non-Service*Move		-0.014		-0.022		-22.441		-0.104	0.075
		[0.081]		[0.262]		[15.485]		[0.038]**	[0.026]**
Manager*Move		-0.113		-0.007		-22.356		-0.091	0.029
		[0.067]+		[0.243]		[13.704]		[0.029]**	[0.019]
Observations	28166	28166	29186	29186	29186	29186	29186	29186	7674

Robust standard errors in parentheses, clustered by person

+ significant at 10%; * significant at 5%; ** significant at 1%

Onless otherwise noted, regressions include all observations with a valid wage change and occupation.

1. Regressions also include the following 7 occupation dummies and interactions of these with stay: Sales, clerical, craft, operative, transportation, laborer farm service, as well as the main effects for prof-non-serv and manager.

2. Regression only includes workers who moved jobs in between wage observations.

Includes the cross-section, non-military male sample of the NLSY from 1979-2000. Only post-transition, full time, non self employed, non enrolled wage observations are included. Transition year is defined by the beginning of the first two-year spell primarily working. Individual must have a valid starting wage at the current employer.

Table 6: Spread of Log Wage Change Residuals[1] by Occupation				
	Squared Residuals[2]		Inter-Quartile Range[3]	
	All	Low Tenure[4]	All	Low Tenure[4]
Stay*Prof non serv	0.100	0.097	0.117	0.133
	[0.045]*	[0.037]**	[0.053]*	[0.061]*
Stay*Manager	0.107	0.103	0.029	0.061
	[0.046]*	[0.037]**	[0.051]	[0.059]
Stay at Employer	-0.112	-0.117	-0.216	-0.200
	[0.042]**	[0.031]**	[0.040]**	[0.047]**
Prof Non-Service	-0.087	-0.057	-0.091	-0.110
	[0.047]+	[0.038]	[0.097]	[0.081]
Manager	-0.098	-0.06	-0.064	-0.119
	[0.047]*	[0.042]	[0.087]	[0.081]
Observations	29186	15711	7084	2787
R-squared	0.02	0.02		

Standard errors in squared residuals panel clustered by person.

Standard errors in inter-quartile range panel obtained by bootstrapping with 5000 repetitions.

+ significant at 10%; * significant at 5%; ** significant at 1%

1. Log wage changes regressed on the following and squared residuals are obtained: Occupation, an indicator for staying and all interactions, a quadratic in age, dummy variables for year tenure, dummy variables for previous-period tenure, change in tenure square, final tenure with previous employer if moves (otherwise 0), education dummies, geographic region and urbanicity dummies, marital status, actual labor market experience, year effects, black and hispanic dummies, industry, current occupation dummies, a dummy for having changed industry, and interactions of current and previous occupation.

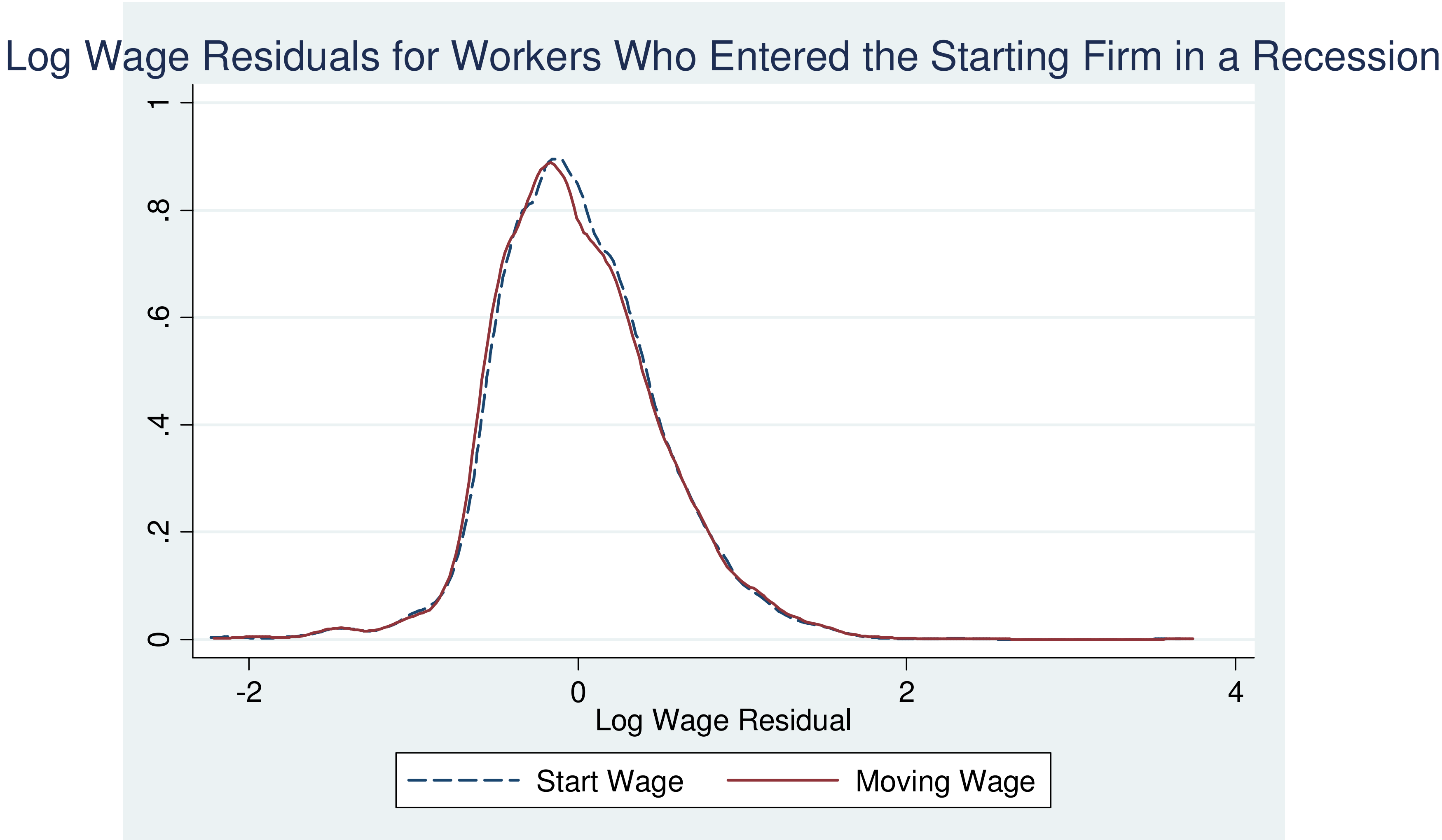
2. Regressions include initial occupation dummies, current occupation dummies, interactions with initial occupation and staying, interactions of current occupation and initial occupation and conrols for race and education. The occupation categories are: Prof-non-serv, manager, sales, clerical, craft, operative, transportation, laborer, farm, service, with prof-serv as the omitted category.

3. Estimates obtained by differencing the coefficients from quantile regressions (75th %ile and 25th %ile) and bootstrapping with 5000 repetitions to obtain standard errors. Quantile regressions include controls specified in note 2, but the sample is restricted to just those whose initial occupation was prof-serv, prof-non-serv or manager for computational ease.

4. Restricted to observations with tenure less than 2 years (in second wage observation).

Includes the cross-section, non-military male sample of the NLSY from 1979-2000. Only post-transition, full time, non self employed, non enrolled wage observations are included. Transition year is defined by the beginning of the first two-year spell primarily working. Individual must have a valid starting wage at the current employer.

Appendix Figure 1:



Appendix Table B1: Data Description

Variable	Description	Codes
Wage	NLSY created measure of hourly rate of pay	CPI adjusted to 2000 dollars, missing if <$1 or >$500.
AFQT	Section2 + Section3 + Section4 + .5*Section5	For the entire NLSY sample, I create means and standard deviations by birth year then standardize each score by these.
Occupation	3-digit 1970 codes, recoded to 1 digit (manager, professional, sales, clerical, craft, operative, transport, labor, farm, service)	Occ/ind are constant w/in a job. Defined by last observation w/in a job. If missing, use second-to-last obs and so forth.
Industry	3-digit 1970 codes, recoded to the standard 15 categories	
White Collar	equals 1 if occ is professional, manager, sales or clerical	
Prof-Serv	Equals 1 if occ is professional and ind is: business, personal, entertainment or professional services	
Prof-non-Serv	Equals 1 if occ is professional and ind is not a service	
Education	Followed responses to education questions year by year, then create constant measure within person equal to max	in regressions, categories are Prof, MA, BA/BS, AA, HS, GED and dropout, also use total years school "Highest Grade"
Tenure	NLSY created measure, weeks tenure as of int date	
Final Tenure	Constant within job	Tenure at last observation of job or number of weeks b/w start and stop date if tenure is missing (use int date as stop if currently working at last obs of job)
Start Date	Constant within job	Equals reported start date or, if missing, interview date at first observation
Stop Date	Constant within job	Reported stop date or, if missing, int date of last observation if not final job
Reason	Survey question, reason left job	Missing if stop year before 1984, 0 if first job, o.w. categories are: layoff/fired, plant closing, end temp/seasonal/program, or quit
ue rate group	National unemployment rate quartile in start year (<5.6, 5.6-6.2, 6.2-7.2, >7.2)	Missing if first job, equals ue rate for previous job if in first wage observation at job ("movers")

Appendix Table B2: Sample Sizes by Group

A: Layoffs v Plant Closings Analysis[1]

	Jobs	Wage Change Observations
First Job	705	2,727
Layoff/Fired	964	2,221
Plant Close	173	411
Job Ended	396	834
Quit	3,381	8,177
Total	5,619	14,370

B: Job-Entry Cohorts Analysis

		Wage Change Observations		
	Jobs	All	Stayer	Mover
0-25%ile UE Rate	2,114	5,498	3,396	2,102
25-50%ile UE Rate	2,711	7,529	4,927	2,602
50-75 %ile UE Rate	2,897	8,195	5,492	2,703
75-100%ile UE Rate	2,921	8,517	5,865	2,652
Total	10,643	29,739	19,680	10,059

C: Occupations Analysis

		Wage Change Observations		
	Jobs	All	Stayer	Mover
Prof-Serv	431	1,473	1,055	418
Prof Non-Serv	360	1,788	1,435	353
Manager	798	3,823	3,054	769
Sales	509	1,372	883	489
Clerical	576	1,712	1,162	550
Craft	2,377	7,031	4,753	2,278
Operative	1,290	3,336	2,118	1,218
Transport	831	2,184	1,385	799
Laborer	1,380	3,141	1,827	1,314
Farm	173	439	276	163
Services	1,206	2,887	1,732	1,155
Total	9,931	29,186	19,680	9,506

1. Restricted to wage changes w/in an employer. Must have valid reason for leaving previous job.

Includes the cross-section, non-military male sample of the NLSY from 1979-2000. Only post-transition, full time, non self employed, non enrolled wage observations are included. Transition year is defined by the beginning of the first two-year spell primarily working. Individual must have a valid starting wage at the current employer.

Appendix Table B3: Summary Statistics by Group

(standard errors in brackets)

	A: Layoffs v Plant Closings[1]			B. Job-Entry Cohorts			C: Occupations			
	All	Layoff /Fire	Plant Closing	All	0-25 %ile	75-100 %ile	All	Prof-serv	Prof non-serv	Manager
Low Wage Change	0.022	0.021	0.020	0.036	0.029	0.040	0.035	0.063	0.037	0.041
	[0.003]	[0.006]	[0.015]	[0.002]	[0.005]	[0.004]	[0.002]	[0.009]	[0.009]	[0.006]
Black	0.125	0.141	0.182	0.121	0.131	0.115	0.121	0.076	0.086	0.069
	[0.003]	[0.007]	[0.016]	[0.002]	[0.004]	[0.004]	[0.002]	[0.008]	[0.008]	[0.005]
Hispanic	0.073	0.114	0.063	0.075	0.075	0.086	0.075	0.049	0.061	0.052
	[0.002]	[0.005]	[0.013]	[0.002]	[0.004]	[0.003]	[0.002]	[0.007]	[0.006]	[0.004]
Age	31.059	31.394	32.606	29.809	32.726	27.808	29.789	31.980	31.466	31.280
	[0.040]	[0.099]	[0.230]	[0.032]	[0.070]	[0.056]	[0.032]	[0.139]	[0.127]	[0.087]
Years School	13.023	12.227	12.204	12.755	12.950	12.625	12.762	15.713	15.031	13.800
	[0.020]	[0.049]	[0.114]	[0.013]	[0.031]	[0.025]	[0.013]	[0.050]	[0.045]	[0.031]
AFQT	0.192	-0.093	-0.138	0.126	0.120	0.145	0.127	0.885	0.863	0.590
(age-adj)	[0.008]	[0.021]	[0.049]	[0.006]	[0.013]	[0.011]	[0.006]	[0.023]	[0.021]	[0.015]
Married	0.548	0.525	0.511	0.501	0.529	0.474	0.503	0.597	0.572	0.615
	[0.004]	[0.011]	[0.024]	[0.003]	[0.007]	[0.005]	[0.003]	[0.013]	[0.012]	[0.008]
Year	1992	1992	1993	1990	1994	1988	1990	1992	1992	1991
	[0.038]	[0.091]	[0.212]	[0.031]	[0.068]	[0.055]	[0.032]	[0.139]	[0.126]	[0.086]
Actual Experience	242.90	296.59	382.67	246.46	366.91	163.14	243.64	203.34	186.00	233.10
(weeks)	[1.893]	[4.093]	[9.519]	[1.412]	[3.143]	[2.526]	[1.420]	[6.268]	[5.689]	[3.890]
Tenure	3.329	2.935	3.236	2.443	1.835	2.816	2.486	2.664	3.316	3.568
(years)	[0.024]	[0.060]	[0.139]	[0.017]	[0.040]	[0.032]	[0.018]	[0.077]	[0.070]	[0.048]
Low Tenure	0.337	0.385	0.328	0.547	0.601	0.525	0.538	0.484	0.379	0.365
	[0.004]	[0.010]	[0.023]	[0.003]	[0.007]	[0.005]	[0.003]	[0.013]	[0.012]	[0.008]
Time b/w	16.467	27.760	19.549	-	-	-	-	-	-	-
Jobs (weeks)	[0.419]	[1.048]	[2.436]							
Prev Job White Collar	0.312	0.197	0.286	-	-	-	-	-	-	-
	[0.004]	[0.010]	[0.023]							
Stayed				0.662	0.616	0.689	0.674	0.716	0.803	0.799
				[0.003]	[0.006]	[0.005]	[0.003]	[0.012]	[0.011]	[0.007]
Occupation Change	-	-	-	0.215	0.240	0.209	0.201	0.109	0.098	0.124
				[0.002]	[0.006]	[0.004]	[0.002]	[0.010]	[0.009]	[0.006]
Industry Change	-	-	-	0.222	0.251	0.208	0.207	0.150	0.125	0.111
				[0.002]	[0.006]	[0.004]	[0.002]	[0.010]	[0.009]	[0.006]
Observations	14370	2221	411	29739	5498	8517	29186	1473	1788	3823

1. Restricted to wage changes w/in an employer. Must have valid reason for leaving previous job.

Includes the cross-section, non-military male sample of the NLSY from 1979-2000. Only post-transition, full time, non self employed, non enrolled wage observations are included. Transition year is defined by the beginning of the first two-year spell primarily working. Individual must have a valid starting wage at the current employer.

Appendix Table B4: Squared Residuals of Log Wage Changes, Human Capital Controls						
	All			**Low Tenure[1]**		
	Original [2]	**Training Control[3]**	**Start Wage Controls[4]**	**Original [2]**	**Training Control[3]**	**Start Wage Controls[4]**
A: Layoffs v Plant Closings[6]						
Full Sample[5]:						
Layoff Coefficent	-0.017	-0.012	-0.017	-0.063	-0.061	-0.06
	[0.012]	[0.012]	[0.012]	[0.028]*	[0.028]*	[0.027]*
White Collar[5]:						
Layoff Coefficent	-0.024	-0.024	-0.026	-0.06	-0.061	-0.067
	[0.017]	[0.016]	[0.017]	[0.034]+	[0.032]+	[0.033]*
B: Job-Entry Cohorts						
Unemployment rate (relative to lowest quartile)						
Stay*75-100%ile	-0.03	-0.03	-0.018	-0.022	-0.022	-0.016
	[0.014]*	[0.014]*	[0.010]+	[0.008]*	[0.008]*	[0.008]+
C: Occupations						
Occupations (relative to prof-serv)						
Stay*prof-non-serv	0.100	0.100	0.075	0.097	0.098	0.059
	[0.045]*	[0.045]*	[0.046]	[0.037]**	[0.037]**	[0.038]
Stay*manager	0.107	0.108	0.081	0.103	0.103	0.061
	[0.046]*	[0.046]*	[0.045]+	[0.037]**	[0.037]**	[0.038]

Robust standard errors in parentheses, clustered by jperson or ob-entry year (in job-entry cohorts)

+ significant at 10%; * significant at 5%; ** significant at 1%

1. Restricted to observations with tenure less than 2 years (in second wage observation).

2. Results taken directly from previous tables.

3. Log wage changes are regressed on all controls specified in previous tables as well as amount of training the worker has participated in up to and including the t-1 year.

4.Log wage changes are regressed on all controls specified in previous tables as well as starting wage at the employer in the second observation of the wage change and its interaction with tenure dummies. I also control for start-year dummies.

5. Excludes outliers. Outliers are defined as having residuals from the first stage outside the bounds of +-1.6 .

6. Restricted to wage changes w/in an employer. Must have valid reason for leaving previous job.

Includes the cross-section, non-military male sample of the NLSY from 1979-2000. Only post-transition, full time, non self employed, non enrolled wage observations are included. Transition year is defined by the beginning of the first two-year spell primarily working. Individual must have a valid starting wage at the current employer.

Appendix Table B5: Characteristics by Job-Entry Unemployment Rate and Staying

Variable	75-100%ile UE Rate			0-25%ile UE Rate			
	Stay	Move	Difference	Stay	Move	Difference	
Highest Grade							
Mean	12.713	12.433	0.28	13.126	12.669	0.457	+
	[0.091]	[0.074]	[0.073]**	[0.050]	[0.041]	[0.069]**	
Squared Residual[1]	4.788	4.485	0.302	6.105	5.544	0.551	
	[0.250]	[0.265]	[0.308]	[0.368]	[0.264]	[0.196]**	
AFQT							
Mean	0.203	0.016	0.188	0.179	0.025	0.155	
	[0.017]	[0.017]	[0.024]**	[0.014]	[0.022]	[0.022]**	
Squared Residual[1]	0.888	0.918	-0.03	1.003	1.004	-0.001	
	[0.034]	[0.026]	[0.034]	[0.009]	[0.015]	[0.015]	
Tenure Lag (weeks)							
Mean	202.185	92.854	109.33	118.103	69.448	48.655	**
	[17.572]	[3.034]	[14.873]**	[14.031]	[6.155]	[10.102]**	
Squared Residual[1]	43464	18179	25285	15779	9111	6668	**
	[4,862]	[1,919]	[3,643]**	[2,154]	[2,214]	[1,982]**	

Robust standard errors in parentheses, clustered by job-entry year

+ significant at 10%; * significant at 5%; ** significant at 1%

Furthest right column indicates statistical significance between difference columns.

Sample is identical to the main regression sample in table 4.

1. Residualized on job-entry fixed effects, staying and all interactions.

Includes the cross-section, non-military male sample of the NLSY from 1979-2000. Only post-transition, full time, non self employed, non enrolled wage observations are included. Transition year is defined by the beginning of the first two-year spell primarily working. Individual must have a valid starting wage at the current employer.

Appendix Table B6: Characteristics by Occupation and Staying

Variable	Prof-Serv Workers				Prof non-Serv Workers			Managers			
	Stay	Move	Difference		Stay	Move	Difference	Stay	Move	Difference	
Highest Grade											
Mean	15.703	15.737	-0.034		15.029	15.040	-0.011	13.794	13.821	-0.026	
	[0.236]	[0.178]	[0.217]		[0.159]	[0.154]	[0.167]	[0.111]	[0.113]	[0.111]	
Squared Residual[1]	8.065	6.739	1.325	+	4.819	5.041	-0.222	4.722	4.964	-0.242	+
	[0.869]	[0.549]	[0.835]		[0.392]	[0.438]	[0.445]	[0.241]	[0.326]	[0.275]	
AFQT											
Mean	0.89	0.874	0.016		0.869	0.838	0.03	0.616	0.486	0.129	
	[0.061]	[0.051]	[0.056]		[0.064]	[0.049]	[0.062]	[0.040]	[0.041]	[0.039]**	
Squared Residual[1]	0.615	0.609	0.005		0.637	0.516	0.121	0.605	0.657	-0.052	
	[0.080]	[0.069]	[0.075]		[0.106]	[0.057]	[0.095]	[0.052]	[0.049]	[0.047]	
Tenure Lag (weeks)											
Mean	162.292	124.704	37.588		190.228	130.198	60.03	215.35	155.512	59.944	
	[10.190]	[7.296]	[10.546]**		[10.012]	[7.606]	[11.461]**	[7.769]	[6.752]	[8.738]**	
Squared Residual[1]	26817	19857	6960		33057	19234	13823	40827	32710	8117	
	[3,268]	[2,824]	[3,579]+		[3,645]	[3,509]	[4,539]**	[2,813]	[3,200]	[3,807]*	

Robust standard errors in parentheses, clustered by person
+ significant at 10%; * significant at 5%; ** significant at 1%

Statistical significance across difference columns is indicated between sets of columns. The furthest right column indicates statistical significance between managers and prof-serv workers.
Sample is identical to the main regression sample in table 6.
1. Residualized on occupation fixed effects, staying and all interactions.

Includes the cross-section, non-military male sample of the NLSY from 1979-2000. Only post-transition, full time, non self employed, non enrolled wage observations are included. Transition year is defined by the beginning of the first two-year spell primarily working. Individual must have a valid starting wage at the current employer.

Appendix Table B7: Squared Residuals of Log Wage Changes, Controlling for Separation Reason

	All		Low Tenure[1]	
	Original [2]	Separation Reason[3]	Original [2]	Separation Reason[3]
A: Job-Entry Cohorts				
Unemployment rate (relative to lowest quartile)				
Stay*75-100%ile	-0.026	-0.029	-0.022	-0.025
	[0.013]+	[0.012]*	[0.012]+	[0.013]+
B: Occupations				
(occupation relative to prof-serv)				
Stay*prof-non-serv	0.096	0.094	0.09	0.088
	[0.051]+	[0.040]*	[0.051]+	[0.040]*
Stay*manager	0.088	0.099	0.088	0.099
	[0.051]+	[0.042]*	[0.051]+	[0.041]*

Robust standard errors in parentheses, clustered by person or ob-entry year (in job-entry cohorts)

+ significant at 10%; * significant at 5%; ** significant at 1%

1. Restricted to observations with tenure less than 2 years (in second wage observation).

2. Results diiffer slightly from previous tables because here all observations are restricted to having a nonmissing reason for leaving previous job, or, if the wage change is within firm, the job must have ended after 1984 so that stayers are a comparable sample to leavers.

3.Log wage changes are regressed on all controls specified in previous tables as well as reason for leaving previous employer if wage change is between firms (otherwise 0). Residuals are squared then regressed on group indicators, a dummy for staying and interactions of these.

Includes the cross-section, non-military male sample of the NLSY from 1979-2000. Only post-transition, full time, non self employed, non enrolled wage observations are included. Transition year is defined by the beginning of the first two-year spell primarily working. Individual must have a valid starting wage at the current employer.