"Training Contracts, Employee Turnover, and the Returns from Firm-sponsored General Training": Online Appendix

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The Online Appendix is organized as follows. Appendix A provides additional discussion and analysis on various issues. Appendix B analyzes a one-period version of the structural model and derives an analytical result. Appendix C provides a detailed exposition of the structural model used in Section 5 of the paper. Appendix D provides additional figures and tables. Appendix E discusses three miscellaneous issues (measuring productivity, our industry phone survey on firm-sponsored CDL training, and the law as it relates to training contracts).

A Additional Discussion and Results

A.1 Impact of Training Contracts: Further Background, Robustness, and Event Study Analysis

12-month contract, further background. While the contract was certified for different training schools at different times, it should be noted that there is not a deterministic relationship between date of certification and when it was phased in to the different states' training centers. Specifically, for the schools in our sample for which the contract was certified, there was a lag of about 4-12 months after certification before the contract came into effect.[1] To examine empirically whether there could be some relation between contract impacts and time between certification and phase-in, we included an interaction term of the 12-month contract with time from certification to phase-in. We found no systematic difference in the impact of the contract according to this difference (i.e., the interaction term was insignificant and close to 0).

In our sample of 5 schools, one school never received the contract (certification was sought, but never received). A manager suggested the state where this school was located had a pro-employee orientation.

18-month contract, further background. As was the case for the 12-month contract, adoption of the 18-month contract was also staggered. However, unlike the 12-month contract, our understanding is that differences in adoption timing for the 18-month contract were more actively chosen by the firm. The contract was first brought into one training school before being brought into other training schools at a particular later date. However, conversations with senior managers suggest that the difference in timing was unlikely to be related to the impact of the 18-month contract. Managers related that the first training school to receive the 18-month contract happened to be located near where the Director of Training was based at the time, thereby suggesting that bringing the contract there first (as opposed to the other training school locations) may have been mostly an issue of convenience. Unemployment was higher at the end of the data period when the 18-month contract is brought in—we account for this with cohort and time fixed effects, as well as controlling for the annual state unemployment rate.

[1] This could have reflected a desire by the firm to try to bring the contract in at the same time while facing the constraint that the states were taking different amounts of time to certify the contracts.

A.2 Contract Enforcement

As discussed in the text, the available data and conversations with managers suggest that roughly 30% of quit penalties were collected. In terms of data on collections, our data are limited to company records on collections from late 2003. In late 2003, the firm was collecting around 20% of quit penalties, though this was early in our sample period, and the collection rate was likely increasing over the sample period. The head of the company's collections department estimated the total collection rate to be 30%. We also had conversations on the subject of collection rates with a Senior Vice President and the Director of Training. One believed the collection rate to be about 33%, whereas the other believed the collection rate to be about 19%.

Managers also explained to us that training schools are considered private colleges, and training contracts may be counted as a form of loan contract.

In terms of how the collection rate matters for the paper's results, the results in Table 5 are qualitatively robust to other values of θ.

A.3 More Details on Data and Sample Construction

Data and Sample Construction. The data are constructed directly from the various personnel files of the firm (for details, see Burks et al. (2008)). When race, gender, or marital status is missing, its value is set to the excluded category. Thus, for race, the categories are Black, Hispanic, and Other (including White, Other race, and Race missing). For gender, the categories are Female and Non-female (including Male and Gender missing). For marital status, the categories are Married and Non-married. When age is missing as a control variable, missing values are set to mean age. When a driver is missing the annual state unemployment (because they are missing state of residence), we include a dummy variable to indicate it being missing.

As described in the main text, the sample is restricted to 5 schools. These 5 schools comprise about 96% of brand-new inexperienced drivers in our sample period.[2] Of the additional schools, there are two of them that we know never received training contracts. One of them was a 3rd party school that the firm contracted with, and the other is a school that primarily focused on providing non-CDL training to drivers who already had CDLs. We exclude these two training schools because the training provided differed (either it was not provided by the firm or it was delivered by people who focused primarily on providing training to other types of drivers), but our results are robust to including these schools. The other schools have small numbers of drivers and we lack information on contract details. Of the 5 schools, 4 are very similar to one another, whereas one is slightly different (our results become even stronger if this 5th school is excluded).

We also eliminate a small number of cases where a driver re-joins the firm having quit previously. Drivers are observed from hire until termination or the end of 2009. The firm stopped hiring new inexperienced drivers at the end of 2008 (due to the economic slowdown), but all drivers are still observed until the end of 2009.

Teams. A small share of driver-weeks involve drivers working in two-person teams (e.g., one person drives while the other sleeps). In our sample for this paper, about 14% of driver-weeks involve a driver working with another driver. For team drivers, the firm equally divides total miles driven among the two drivers in the payroll data provided to us. We control for whether a driver is a team driver as part of the work type controls.

[2] This number is conditional on driver school code being non-missing. Including drivers where school code is missing, these 5 schools comprise about 91% of brand-new inexperienced drivers in our sample period.

A.4 Other Papers Using Data from Firm A

In a paper written after the results from the current paper had already been released, we studied the phenomenon of hiring through employee referrals (Burks et al., 2015). Specifically, we combined the full dataset from Firm A with data from 8 other firms, and we used this to study differences across referred and non-referred employees. Referral status is uncorrelated with dummies for the 12-month and 18-month contract;[3] therefore, excluding referral status from this paper's analysis should not affect this paper's findings. The sample in the present paper differs in that we restrict to newly trained truckers and we do not restrict attention to individuals with non-missing referral status.

Other papers have used data on a subset of roughly 1,000 Firm A workers (also called the "New Hire Panel" in other papers) to study various topics, including social preferences (Anderson et al., 2013), cognitive skills (Burks et al., 2009), and personality (Rustichini et al., 2012). Those papers do not relate to the present paper and see the Appendix in Hoffman and Burks (2017) for further details on those papers.

B One Period Model

In this section, we present a model of training contracts and turnover to accompany the discussion in Section 2 and derive an analytical result. We show that allowing firms to use training contracts reduces quitting and increase the profitability of training. The model is a 1-period version of our structural model in Hoffman and Burks (2017), abstracting away from dynamics and worker heterogeneity.[4] The model is fairly similar to that in Peterson (2010), with one difference being that we assume monopsony in the market for training whereas Peterson (2010) assumes perfect competition. Both our papers allow for competition in the post-training labor market.

Consider a firm which trains its workers. Workers are risk-neutral and have an initial productivity of zero at the firm and a pre-training outside option of r. A training investment is available at cost c that raises productivity from 0 to η, where $\eta > r$. Workers have some non-pecuniary taste for the job ε, which they learn after training. We assume that ε has a distribution function F and has support over the entire real line. Defining $\Psi(x) = 1 - F(x)$, we assume that the function $x \mapsto x\Psi^{-1}(x)$ is concave. This property is satisfied by many distributions including the uniform and normal distributions. If the firm chooses to train, it also chooses a piece rate w to pay, so the worker's total earnings are $W = w\eta$. The firm may also employ a training contract k, which is a penalty the worker pays if they quit. If the worker quits, they receive an outside option of $\overline{W}$ minus any training contract k. We assume only that the outside option after training is greater than or equal to the worker's outside option before training $\left(\overline{W} \geq r\right)$. The case of $\overline{W} = r$ corresponds to the worker choosing whether to go to another occupation whereas $\overline{W} = \eta$ may correspond to the worker choosing to leave for another firm within the same occupation (if training is portable across firms, but occupation-specific). We can also think of $\overline{W} = r$ as specific training and $\overline{W} = \eta$ as fully general training. Recognizing that enforcement of the contract may be imperfect, we allow that only a share $\theta \in [0, 1]$ of the contract is collected (the firm collects θk). (Our results hold for

[3] That is, we regressed referral status on the contract variables and controls, and the contract coefficients were statistically insignificant.

[4] However, the model here is also more general in that it uses a more general distribution for the taste shocks. In addition, the model is an optimal contracting problem. Thus, we show that allowing training contracts increases training profits, even when firms are optimally setting contracts. Many models of firm-sponsored general training have two periods, see the review in Acemoglu and Pischke (1999a). Our 1-period model takes the 2-period training model and collapses the first period of training to a single point in time. That is, we make the assumption that training occurs instantaneously, which is consistent with the brief nature of training in trucking.

the case of perfect enforcement, $\theta = 1$, unless stated otherwise.) We assume, however, that the training contract is experienced fully by the worker (that is, the worker suffers a utility loss of k after quitting). That is, although the worker is initially credit-constrained, we assume after training that the worker can be penalized, either by making payments to the firm (which the worker can do with either increased income or credit access obtained because of training) or other means (e.g., damage to the worker's credit score or utility loss from pestering).[5] The timing of the model is as follows:

1. The firm chooses whether to train, and if so, sets the worker's piece rate, w, and the level of the training contract, k.
2. The worker decides whether or not to accept the contract (of w, k, and receiving training), and training occurs.
3. The taste shock ε is realized and the worker decides whether to quit.
4. Payoffs are realized.

In this baseline model, workers have rational beliefs about their post-training productivity. Specifically, workers believe their post-training productivity will be η. With rational beliefs, it is the same for the firm to set realized earnings, W, as it is for the firm to set the piece rate, w. The firm's problem can be written as:

$$\max_{W,k}(1 - F(-W - k + \overline{W})) * (\eta - W) + F(-W - k + \overline{W})\theta k - c$$

$$E \max\left(W + \varepsilon, \overline{W} - k\right) \geq r$$

Proposition 1 *Allowing firms to use training contracts increases the profitability of training and increases retention compared to when training contracts are not available.*

Proof. The IR constraint must bind at an interior solution. To see why, differentiate the Lagrangean to get

$$f\left(-W - k + \overline{W}\right)(\eta - W - \theta k) - \left(1 - F\left(-W - k + \overline{W}\right)\right) + \lambda \frac{\partial Emax}{\partial W} = 0$$

$$f\left(-W - k + \overline{W}\right)(\eta - W - \theta k) + \theta F\left(-W - k + \overline{W}\right) + \lambda \frac{\partial Emax}{\partial k} = 0$$

If $\lambda = 0$, an interior solution exists only if $\left(1 - F\left(-W - k + \overline{W}\right)\right) = -\theta F\left(-W - k + \overline{W}\right)$, which is not possible for $\theta > 0$.[6] Because the IR constraint cannot hold with equality while setting $k = 0$ (since $\overline{W} \geq r$, and $Pr(W + \varepsilon > \overline{W}) > 0$ since ε has full support), $k = 0$ cannot be optimal.

To analyze retention, let P denote the retention probability. Note then that $W = \left(\bar{W} - k - \Psi^{-1}(P)\right)$. Profits are then given by:

$$P \times (\eta - W) + (1 - P)\theta k - c = P \times \left(\eta - \left(\bar{W} - k - \Psi^{-1}(P)\right)\right) + (1 - P)\theta k - c$$
$$= P(\eta - \bar{W}) + k(P + (1 - P)\theta) + P\Psi^{-1}(P).$$

[5] We believe our assumption, that drivers act as if the utility cost of quitting is equivalent to the utility loss from paying the contract penalty, is reasonable in our setting; see the discussion in Hoffman and Burks (2017) for more discussion on this. Our model conclusions should still hold if the worker's utility cost for quitting is less; a fine of \$2 of which the firm collects 25% and the worker pays 50% in utiles operates the same as a fine of \$1 of which the firm collects 50% and the worker pays 100% in utiles. By the term *training profits*, we mean the profits a firm receives from hiring and training one worker (vs. not hiring and training the worker). Although we talk here of the *profitability* of general training, we could also frame the model to deliver results on the *probability* of training. Specifically, instead of assuming a fixed cost of training, c, we could assume that c was a random variable.

[6] The boundary solutions for the unconstrained problem are to have W go to minus infinity and k go to positive infinity faster (all workers stay and get paid minus infinity) or to have W go to minus infinity and have k go to positive infinity slower (all workers quit and the firm collects infinity from them). Both of these solutions violate the IR constraint.

Note that the IR constraint can be written as $r \leq Emax\left(\bar{W} - \Psi^{-1}(P) - k + \varepsilon, \bar{W} - k\right)$ or as $r \leq \bar{W} - k + Emax\left(\varepsilon - \Psi^{-1}(P), 0\right)$. By inspection, the right hand is strictly decreasing in k, but also strictly increasing in P. Thus, the IR constraint defines a strictly increasing function $k = k(P)$.

In the case where $k = 0$, the first order condition is

$$\eta - \bar{W} + \Psi^{-1}(P) + P\Psi^{-1\prime}(P) = 0\,. \tag{4}$$

When the firm can optimally set k, the first order condition is

$$\eta - \bar{W} + \Psi^{-1}(P) + P\Psi^{-1\prime}(P) + k'(P) \times (P + (1-P)\theta) + k(1-\theta) = 0. \tag{5}$$

Given that $k'(P) \times (P + (1-P)\theta) + k(1-\theta)$ is positive for all P and that $\Psi^{-1}(P) + P\Psi^{-1\prime}(P)$ is decreasing in P (by the concavity of $P\Psi^{-1}(P)$), it follows that the P that solves Equation (5) (where the firm optimally sets k) is greater than the P that solves Equation (4) (where $k = 0$). ■

C Dynamic Structural Model

Below is the exposition of the structural model in Hoffman and Burks (2017). As of March 2017, the text here is currently the same as in Hoffman and Burks (2017). However, we do not provide here detailed discussion regarding model assumptions; please see Hoffman and Burks (2017) for justification on the different assumptions made, particularly the assumptions about non-standard beliefs.

The time horizon is infinite and given in weeks 1, 2, ... Workers have baseline productivity η, which is distributed $N\left(\eta_0, \sigma_0^2\right)$. Workers are paid by a piece rate, w_t, that depends on their tenure. Workers know the piece rate-tenure profile, and believe that this profile will not be changed by the company at some future date.[7] A worker's weekly miles, y_t, are distributed $N\left(a(t) + \eta, \sigma_y^2\right)$,[8] and weekly earnings are thus $Y_t = w_t y_t$. $a(t)$ is a known learn-by-doing process, which we specify below. The worker's outside option is r_t and also depends on his tenure. Every period t, the worker makes a decision, d_t, whether to stay ($d_t = 1$) or to quit ($d_t = 0$). Workers make the decision to quit in t having observed their past miles $y_1, y_2, ..., y_{t-1}$, but not their current week miles, y_t. Workers and firms are assumed to be risk-neutral and to have a discount factor given by δ.[9]

Stay-or-Quit Decisions. Workers make their stay-or-quit decisions every period to maximize perceived expected utility:

$$V_t(\mathbf{x}_t) = \max_{d_t, d_{t+1}, \ldots} E_t\left(\sum_{s=t}^{\infty} \delta^{s-t} u_s\left(d_s, \mathbf{x}_s\right) | d_t, \mathbf{x}_t\right). \tag{6}$$

where $\mathbf{x}_t$ is the vector of state variables ($\mathbf{x}_t$ includes past miles, $y_1, ..., y_{t-1}$, and is detailed further below). (6) can be written as a Bellman Equation: $V_t(\mathbf{x}_t) = \max_{d_t} E_t\left(u_t\left(d_t, \mathbf{x}_t\right) + \delta V_{t+1}(\mathbf{x}_{t+1}) | d_t, \mathbf{x}_t\right)$.

The per-period utility from staying at the job is equal to the sum of the worker's non-

[7] Assumptions of this form are standard in structural labor and personnel economics, and allows us to avoid having to specify beliefs over possible future firm policy changes. We believe the assumption is reasonable in our setting, given it is not common for the firm to make large changes in the pay schedule.

[8] Assuming that signals are normally distributed is standard in structural learning models (see the survey by Ching et al. (2013)). Visually, the distribution of signals (miles) among all workers has a bell shape centered close to around 2,000 miles, suggesting this assumption is reasonable (and that the distribution is closer to normal than to log-normal or uniform).

[9] Risk neutrality is assumed in many dynamic learning models (e.g., Crawford and Shum, 2005; Nagypal, 2007; Stange, 2012; Goettler and Clay, 2011), though not in all (for examples with risk aversion, see the survey by Ching et al. (2013)). Coscelli and Shum (2004) show that risk parameters are not identified in certain classes of learning models.

pecuniary taste for the job, earnings, and an idiosyncratic shock:

$$u_t\left(1,\mathbf{x}_t\right)=\alpha+w_t y_t+\varepsilon_t^S,$$

where α is the worker's non-pecuniary taste for the job, and ε_t^S is an i.i.d. idiosyncratic error unobserved to the econometrician (but observed by the worker) with an Extreme Value-Type 1 distribution and scale parameter τ. Since workers likely differ unobservedly in taste for the job, we assume there is unobserved heterogeneity in non-pecuniary taste for the job, α, with α drawn from a mass-point distribution (Heckman and Singer, 1984).

If the worker quits, he may have to pay a fine associated with the training contract. Let the vector $\mathbf{k}$ denote the training contract, with k_t the penalty for quitting at tenure t. The utility from quitting is the fine, plus the discounted value of his outside option, plus an idiosyncratic shock:

$$u_t\left(0,\mathbf{x}_t\right)=-k_t+\frac{r_t}{1-\delta}+\varepsilon_t^Q,$$

where ε_t^Q is an i.i.d. unobserved idiosyncratic error with the same distribution as ε_t^S.[10] Let $V_t^S \equiv E_t\left(u_t\left(1,\mathbf{x}_t\right)+\delta V_t(\mathbf{x}_{t+1})|1,\mathbf{x}_t\right)$ and $V_t^Q \equiv E_t\left(u_t\left(0,\mathbf{x}_t\right)+\delta V_t(\mathbf{x}_{t+1})|0,\mathbf{x}_t\right)$ be the choice-specific value functions for staying and quitting, respectively. Plugging in for $u_t\left(1,\mathbf{x}_t\right)$ and $u_t\left(0,\mathbf{x}_t\right)$, the choice-specific value functions are given by:

$$\begin{aligned}
V_t^Q &= -k_t+\frac{r_t}{1-\delta}+\varepsilon_t^Q \equiv \overline{V}_t^Q+\varepsilon_t^Q \\
V_t^S &= \alpha+E_t(w_t y_t|\mathbf{x}_t)+\delta E(V_{t+1}(\mathbf{x}_{t+1})|\mathbf{x}_t)+\varepsilon_t^S \equiv \overline{V}_t^S+\varepsilon_t^S,
\end{aligned}$$

and the Bellman Equation can be re-written as $V_t(\mathbf{x}_t)=\max_{d_t\in\{0,1\}}\left(V_t^S\left(\mathbf{x}_t\right),V_t^Q\left(\mathbf{x}_t\right)\right)$.

Agents gradually learn their productivity as more and more productivity signals are observed. Thus, after a sufficiently large number of periods, T, the value function can be approximated by the following asymptotic value functions:

$$\begin{aligned}
V^Q &= \frac{r_T}{1-\delta}+\varepsilon^Q \equiv \overline{V}^Q+\varepsilon^Q \\
V^S &= \alpha+w_T\eta+\delta E(V(\mathbf{x}')|\mathbf{x})+\varepsilon^S \equiv \overline{V}^S+\varepsilon^S \\
V(\mathbf{x}) &= \max_{d\in\{0,1\}}\left(V^S\left(\mathbf{x}\right),V^Q\left(\mathbf{x}\right)\right)
\end{aligned}$$

Belief Formation. In a standard normal learning model, a worker's beliefs about his period t productivity equals the weighted sum of his prior and his demeaned average productivity to date:

$$E(y_t|y_1,...,y_{t-1})=\frac{\sigma_y^2}{(t-1)\,\sigma_0^2+\sigma_y^2}\eta_0+\frac{(t-1)\,\sigma_0^2}{(t-1)\,\sigma_0^2+\sigma_y^2}\frac{\sum_{s=1}^{t-1}y_s-a(s)}{s-1}+a(t) \tag{7}$$

As t increases, the agent eventually shifts all the weight from his prior to his average productivity signals. We augment the standard learning model in two ways. First, we allow for agents to be overconfident: instead of believing that their productivity, η, is drawn from a distribution $N\left(\eta_0,\sigma_0^2\right)$, agents believe η is drawn from a distribution $N\left(\eta_0+\eta_b,\sigma_0^2\right)$. Second, we allow for agents to have a perception of signal noise that may be different from the true signal noise: workers perceive the standard deviation of weekly productivity signals to be $\widetilde{\sigma_y}$ instead of σ_y. With these two assumptions, an agent's subjective expectation of his productivity, denoted by E^b (where b

[10] Even though only a portion of the penalties owed were collected, as described in Section 3, we assume that drivers act as if the utility cost of quitting is equivalent to the utility loss from paying the contract penalty. We believe this assumption is reasonable. Firm A was very firm with new drivers about its intention to collect money owed upon a quit. After a quit, drivers who did not pay faced aggressive collection contacts by both Firm A and collection agencies, as well as the reporting of delinquency to credit agencies. As a robustness check, we have experimented with estimating versions of the model assuming drivers act as if the utility loss from quitting is 0.3 times the penalty. Model fit tended to be less good. Indeed, our preferred model still fails to fully match the quitting spike at one year, as seen in Figure 2 of Hoffman and Burks (2017).

stands for belief), is:

$$E^b(y_t|y_1,...,y_{t-1}) = \frac{\widetilde{\sigma_y}^2}{(t-1)\,\sigma_0^2 + \widetilde{\sigma_y}^2}(\eta_0 + \eta_b) + \frac{(t-1)\,\sigma_0^2}{(t-1)\,\sigma_0^2 + \widetilde{\sigma_y}^2}\frac{\sum_{s=1}^{t-1} y_s - a(s)}{s-1} + a(t) \qquad (8)$$

If η_b is greater (less) than zero, then agents exhibit positive (negative) mean bias or overconfidence (underconfidence). As more signals come in, agents will learn not to be overconfident, eventually putting zero weight on $(\eta_0 + \eta_b)$. The speed at which this occurs, however, will be determined by $\widetilde{\sigma_y}$.

We allow that workers' reported subjective beliefs include some measurement error, as accurately reporting one's beliefs about productivity may be unusual or unfamiliar for a worker. We assume that reported beliefs equal underlying subjective beliefs plus a normally distributed error. The reported subjective belief, b_{it}, of driver i at tenure week t is distributed: $b_{it} \sim N\left(E^b\left(y_{it}|y_{i1},...,y_{it-1}\right), \sigma_b^2\right)$.

Summary of Within Period Timing. The within period timing in week t is as follows:

1. Workers form beliefs b_t given past miles $y_1, y_2, ..., y_{t-1}$.
2. ε_t^S and ε_t^Q are realized and workers decide whether or not to quit.
3. y_t is realized, if they do not quit.

Learning by Doing and Skill Accumulation. Productivity increases with the learning by doing function $a(t) = 2a_1 * (\Lambda(a_2 t) - .5)$, where $\Lambda(x) = \frac{e(x)}{1+e(x)}$ and t is worker tenure in weeks. $a(t)$ depends only on tenure; thus, the speed of learning by doing does not depend on the number of miles driven or on the ability of the driver. Workers fully anticipate the path of $a(t)$.[11]

We also account for skill accumulation following CDL training. After CDL training at Firm A, drivers do "on-the-job training" which includes driving with an experienced driver riding along. We use a length of 5 weeks for on-the-job training.[12] We account for the possibility that drivers may gain valuable skills during this time: we assume the outside option over time is $r_t = r - \frac{6-min\{t,6\}}{5}s_0$. We fix r using outside data, while s_0, the value of skills from on-the-job training, is estimated. (Besides allowing for skill accumulation during the first 5 weeks, we alternatively estimate the model allowing for continuous skill accumulation: $r_t = r + 2\theta_1 * (\Lambda(\theta_2 t) - .5)$, where $\Lambda(x) = \frac{e(x)}{1+e(x)}$, and θ_1 and θ_2 are parameters to estimate.)

Solving the Model. The state variables consist of past miles, the piece rate, the training contract, taste heterogeneity, a person's level of overconfidence, a vector of observable additional characteristics (X), and the idiosyncratic shocks: $\mathbf{x}_t = (y_1, ..., y_{t-1}, \mathbf{w}, \mathbf{k}, \alpha, \eta_b, X, \varepsilon)$. The model can allow for heterogeneity in taste for the job and/or in overconfidence. To solve the model, we first solve for the asymptotic value functions (after all learning has taken placed) using value function iteration. With the asymptotic value functions in hand, backward recursion can then be applied to solve the dynamic programming problem.

This ends the portion of text that is the same as in Hoffman and Burks (2017) (as of March 2017).

[11] The logistic functional form is consistent with Jovanovic and Nyarko's (1996) micro-founded model of learning by doing in which the speed of learning decreases over time, as well as the empirical results on tenure and productivity in Shaw and Lazear (2008). Here, a_1 is the total amount by which productivity increases and a_2 indicates the speed of learning by doing. We believe our assumption that workers fully anticipate the learning by doing process is reasonable in our setting. In interviews, managers often referred to a steep "learning curve" for rookie drivers.

[12] During this time, drivers often are paid by flat salary instead of by mile. We use a flat salary of $375 per week during on-the-job training. We also assume drivers do not begin learning about their productivity until after 5 weeks.

C.1 Identification and Estimation

Identification. While the parameters in the structural model are jointly identified, we briefly discuss some of the main features of the data that enable us to identify various parameters. The productivity parameters are identified primarily by our productivity data on worker productivity over time. For example, the larger the persistent differences across drivers in true productivity, the larger the estimated value of σ_y. For the belief parameters, our subjective beliefs data play a key role. For example, if we observe that people seem to learn about their productivity much slower than predicted by Bayes' Rule, this will show up in a higher value of $\widetilde{\sigma_y}$. The taste heterogeneity parameters are identified through differences between model-predicted and actual quitting behavior. For example, if we observe a driver who has very low productivity but remains with the firm, that driver would be likely to have a high taste for the job. τ, the scale parameter for the idiosyncratic shocks, is identified based off of how close is model-predicted quitting behavior to that observed in the data (as higher values of τ serve to flatten the quit hazard over time).

Estimation. We estimate the model using maximum likelihood. We use an extension of the Rust (1987) canonical nested fixed point algorithm. We assume that learning about productivity is complete after $T = 130$ weeks.[13] The outside option, r, is assumed to be given by the median full-time earnings of 35-year old males with a high school degree in the 2006 March CPS, as this mirrors the profile of the "median" driver in Hoffman and Burks (2017). This value is \$32,000 per year, which we convert to a weekly wage level of \$640.[14] Under the training contracts, the quit penalties varied slightly by training school. In addition, a significant interest rate may also have been assess if drivers were not able to pay the penalty owed upon a quit. For the structural analysis, we assume a penalty of \$3,750 for the 12-month contract, and we assume a penalty of \$5,250 decreasing linearly over 18 months for the 18-month contract. For the 18-month contract, we also assume a weekly payroll deduction of \$12.50 (for 72 weeks starting in week 5), as well as a bonus of \$1,000 paid after 2 years. Parameter estimates are provided below in Table D2. Full details on the method of estimation are provided in Hoffman and Burks (2017).

C.2 Calculating Firm Profits and Worker Welfare

Following Hoffman and Burks (2017), based on consultation with Firm A managers, we assume that $P - MC = \$0.70$ per mile, $FC = \$650$ per week, $\theta = 0.3$, and $TC = \$2,500$ for the new inexperienced workers that we are studying. We use a weekly discount factor of $\delta = 0.9957$ (corresponding to an annual discount factor of 0.80), as we found that the model fit was slightly worse with higher discount factors (see Appendix Table F1 in Hoffman and Burks (2017)). While an annualized discount factor of 0.80 may seem "low," similar or lower annualized discount factors are not uncommon in studies of blue-collar or low/medium-skilled workers (e.g., Paserman, 2008; Fang and Silverman, 2009; Warner and Pleeter, 2001). To avoid having conclusions driven by differences in discount factors between workers and the firm, we equate the firm's discount factor to be the same as the worker's.

As discussed further in Hoffman and Burks (2017), we make various simplifications in calculating profits. In addition to excluding firing decisions, we ignore several components of profits, including hiring costs (including recruiting costs and any hiring bonuses), vacancy costs, trucking accident costs, employee referral bonuses, driver benefits, and non-mileage driver pay (including

[13] Appendix Table F1 in Hoffman and Burks (2017) shows that results are robust to allowing learning to occur for $T = 200$ weeks.

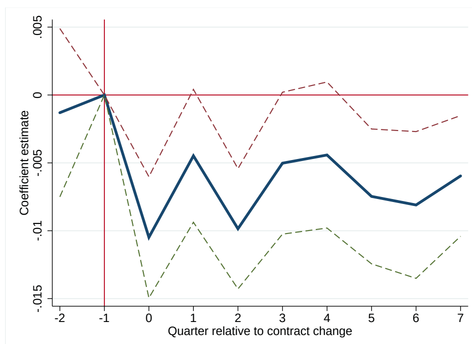
[14] Appendix Table F1 in Hoffman and Burks (2017) shows that the main structural estimates are robust to assuming a higher outside option level.

driver bonuses). Rather, we make an assumption regarding the overall weekly fixed cost. For some of these components, there is only limited data, and it would be quite challenging for the structural model to try to incorporate all of them. However, the different contract simulations in this paper seem generally qualitatively robust to alternative assumptions.

Our model generalizes Bayes' Rule, so that workers are allowed to have non-standard beliefs. Despite having non-standard beliefs, workers have standard preferences. Thus, we calculate worker welfare simply by summing up realized worker welfare across the different weeks. We therefore avoid complications in calculating welfare that arise when workers have non-standard preferences.

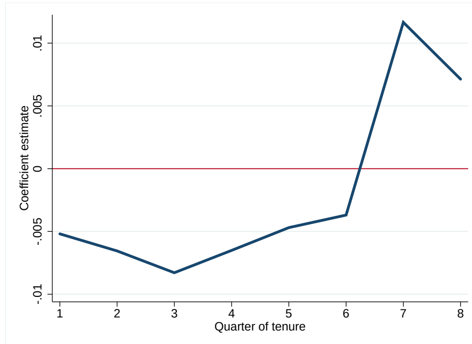
D Additional Tables and Figures

Figure D1: Event Study Impacts of the 12-Month Contract, Restrict to Training School with Longest Pre-Period (with 95% Confidence Intervals)



Notes: This figure is similar panel (a) of Figure 3. The difference is that we restrict to the training school with the longest pre-period before the 12-month contract (it changed from no contract to the 12-month contract in fall 2002) among the training schools eventually receiving the 12-month contract. In addition, as we only have one training school here, we do not control for month-year of hire fixed effects or current quarter-year fixed effects. As in panel (a) of Figure 3, the plotted coefficient for "-2" is an indicator for event time equal to "-3" or to "-2" (we combine them together to increase power).

Figure D2: The Impact of Training Contracts on Quitting by Quarter of Tenure using Simulated Data, Assuming that Drivers Believe the 18-month Contract is a Flat Cliff instead of Pro-Rated



Notes: This figure is similar panel (b) of Figure 2. The difference is that we assume here that drivers believe the 18-month Contract is a flat cliff instead of pro-rated.

Table D1: Impact of the Training Contracts on Firing – Cox Model, Diff-in-Diff

	(1)	(2)	(3)	(4)
12 contract	-0.099	-0.100	-0.093	-0.098
	(0.082)	(0.082)	(0.082)	(0.082)
18m contract	-0.042	-0.040	-0.003	-0.009
	(0.113)	(0.113)	(0.113)	(0.114)
Unemployment controls	No	Yes	Yes	Yes
Productivity controls	No	No	Yes	Yes
Demographic controls	No	No	No	Yes

Notes: This table mirrors columns 1-4 of Table 2 (with the same controls in column 1 here as in column 1 in Table 2, etc.). The difference is that the failure event in the Cox proportional hazard model is getting fired instead of quitting. The estimates show no evidence that the contracts affected firing. Also, when the firing hazards are plotted, they look similar under the three contract regimes. * significant at 10%; ** significant at 5%; *** significant at 1%

Table D2: Structural Estimates (basis for simulations)

		(1)
	Productivity and Skill Parameters	
η_0	Mean of prior productivity dist	2025
		(17)
σ_0	Std dev of prior productivity dist	286
		(11)
σ_y	Std dev of productivity shocks	706
		(3.6)
s_0	Skill accumulation in first 5 weeks	8.6
		(4.4)
	Taste UH Parameters	
μ_1	Mass point 1 of taste UH	-260
		(14)
μ_2	Mass point 2 of taste UH	-135
		(13)
μ_3	Mass point 3 of taste UH	135
		(41)
p_1	Probability type 1	0.34
		(0.07)
p_1	Probability type 2	0.43
		(0.06)
	Belief Parameters	
η_b	Belief bias	589
		(28)
$\widetilde{\sigma_y}$	Believed std dev of productivity shocks	1888
		(136)
σ_b	Std dev in beliefs	298
		(1.4)
	Scale Parameter	
τ	Scale param of idiosyncratic shock	2208
		(350)
	Log-likelihood	-90865
	Number of workers	699

Notes: This table presents estimates of the structural parameters. The idiosyncratic shock, skill gain, and taste parameters are given in terms of dollars whereas the productivity and belief parameters are given in terms of miles. "Taste UH" stands for unobserved heterogeneity in taste for the job. Standard errors are in parentheses and are calculated by inverting the Hessian. A weekly discount factor of 0.9957 is assumed for workers and firms, corresponding to an annual discount factor of 0.8. The data are from 699 drivers in the data subset, all of whom face the 12-month training contract.

E Miscellaneous

E.1 Legal Issues About Training Contracts

We describe how training contracts of different forms are generally legal in the US. We draw primarily on the law articles by Kraus (1993, 2008). Although we use the word "penalty" to describe a training contract, courts have ruled that the amount owed under training contracts for early exit must be reasonable and no larger than the cost of training for firms. However, defining the actual "cost" of training is a difficult matter (e.g., there is the issue of average versus marginal cost, as well as the fact that one of the main costs of training is the time spent by employees working with trainees, which is hard to price). Courts have often allowed training contracts with seemingly large amounts owed. For example, in *Tremco Incorporated v. Kent*, a case where a roofing products sales company sought the recovery of $42,000, the amount owed under a contract if a roofing salesmen trainee did not fulfill three years of service, the court deemed the contract to be enforceable.[15] Training contracts of many different lengths are allowed and observed. For example, in trucking, the duration of training contracts is often 6-24 months, whereas for police officers, contracts of 5 years are sometimes used. In addition, courts have generally held that enforceability does not depend on whether termination penalties decrease with tenure, holding that employees have the ability to bargain over this issue before signing a contract; see e.g. Judge Richard Easterbrook's opinion in *Heder v. City of Two Rivers*. Training contracts are enforced across the US, which is different than is the case for other mobility-restricting labor contracts like non-compete agreements, where enforcement varies by state (e.g., Lavetti et al., 2013). Kraus (1993, 2008) also report instances of training contracts in the UK and Iceland.

E.2 Measuring Productivity

Firm A drivers are mostly paid by the mile. Drivers also get small additional payments for non-miles related tasks (e.g., loading and unloading, going through customs, scales weighing, working on trailers, and training other drivers). Some drivers are paid based on salary or based on their activities instead of being paid by the mile (for example, drivers who work as full-time instructors at the training schools).

According to the US federal hours-of-service regulations, drivers in firms like Firm A are permitted to work up to 70 hours over 8 days. See:
http://www.fmcsa.dot.gov/rules-regulations/topics/hos/index.htm, accessed in Oct. 2010. This translates to a federal legal maximum of roughly 60 hours per calendar week.

Beyond tenure with the firm, the driver's payment per mile rises with experience outside the firm. However, the distinction is not relevant in our case, as the drivers we study are new to the industry.

For the period of time that we study, Firm A had basic on-board computers (Hubbard, 2003), but drivers were still responsible for all time management and route planning. Firm A is a leading firm with a large number of available loads. To our understanding, there is not systematic assignment of desirable loads to good drivers. Further, there is no scope for boss-driver favoritism, because the driver's boss does not assign him loads.

There is a small amount of measurement error in our productivity measure, miles per week. Miles per week is imperfectly observed since miles are only recorded when a driver reaches their destination. Hoffman and Burks (2017) further detail the source of the measurement error; explain how it can be corrected; and show it has little impact on the estimates and conclusions in that paper.

[15] There are limits, however. *Heartland Securities Corp. v. Gerstenblatt* dealt with a case where new college graduates were provided computer training by an online brokerage company, in exchange for promising to stay with the company for two years, with a penalty of $200,000 for leaving. The court held this very large contract to be unenforceable.

E.3 Industry Survey on CDL Training

We did an industry survey of large trucking firms. We find that other firms provide training under training contracts (like Firm A), but that training is concentrated among the largest firms.

We conducted phone interviews with the 20 largest dry-van and 10 largest refrigerated trucking companies in the US.[16] At each company, we asked to speak to someone who was familiar with the details of driver training, usually the director of human resources, the director of training, or a driver recruiter. We collected panel data on each firm's training practices from 2001-2010.[17] For each year, we asked whether the firm provided CDL training and whether a training contract was used. Our findings from the survey are:

1. 16 of 30 firms report providing CDL training at some point from 2001-2010. This could be from operating their own training school or from a partnership with a 3rd party school where the firm paid for the worker's training.[18]
2. Larger firms are more likely to train. A 1 log-point increase in firm revenue is associated with a 22 percentage point increased probability of training.[19]
3. When asked why they choose to provide firm-sponsored training, firms often answer that they do so because it is often difficult to find enough qualified drivers.
4. Training contracts are widely used by firms that provide CDL training. There is significant variation across firms in the form of training contracts used, though there are common elements. At one firm, drivers owe $2,995 if they quit in the first year. At another firm, the training contract lasts 26 months. Workers who quit during the first 13 months are required to pay back $3900 to the firm. After 13 months, the amount owed is reduced by $300 per month for 13 months; half of the monthly $300 deduction is deducted from the worker's paycheck. At another firm, the training contract lasts 12 months. Drivers who quit in the first 6 months are required to pay $3500 to the firm, and drivers who quit in months 7-12 are required to pay $1750.

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[16] The list of companies was obtained from Transport Topics (2009), a leading industry trade journal. Using the journal, we picked the largest 30 companies (20 in dry-van, 10 in refrigerated) after excluding several firms that were (1) Primarily comprised of drivers that owned their own trucks (owner-operators), (2) Primarily providers of logistic or staffing services instead of trucking services, or (3) Canadian companies. We were able to interview someone at all 30 companies, though some companies required multiple follow-up phone calls.

[17] When the person we spoke with was not familiar with what the company had done in the past, we tried to conduct a second interview with someone who was. Despite this, however, some firms were not able to provide longer-term information. In addition, the survey is based on recollections of the person we spoke to.

[18] In addition or as an alternative to providing CDL training, many companies offer tuition reimbursement programs, where drivers can pay for their training on their own, and receive payments from the company over time.

[19] Specifically, this is from a linear probability model regressing whether a firm offered CDL training in a given year on log 2008 revenue and a control for dry-van vs. refrigerated status. The coefficient on log 2008 revenue is 0.22 ($p = 0.04$).

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