

Training Contracts, Worker Overconfidence, and the Provision of Firm-Sponsored General Training*

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Abstract

Training by firms is a central means by which workers accumulate human capital, yet firms may be reluctant to train if workers can quit and use their gained skills elsewhere. “Training contracts” that impose a penalty for premature quitting can help alleviate this inefficiency. This paper studies training contracts in the U.S. trucking industry where they are widely used, focusing on data from one leading firm. Exploiting two plausibly exogenous contract changes that introduced penalties for quitting, I confirm that training contracts significantly reduce quitting. To analyze the optimal design of training contracts and their welfare consequences, I develop and estimate a structural learning model with heterogeneous beliefs that accounts for many key features of the data. The estimation combines weekly productivity data with weekly subjective productivity forecasts for each worker and reveals a pattern of persistent overconfidence whereby many workers believe they will achieve higher productivity than they actually attain. If workers are overconfident about their productivity at the firm relative to their outside option, they will be less likely to quit and more likely to sign training contracts. Counterfactual analysis shows that workers’ estimated overconfidence increases firm profits by over \$7,000 per truck, but reduces worker welfare by 1.5%. Banning training contracts decreases profits by \$4,600 per truck and decreases retention by 25%, but increases worker welfare by 4%. Despite the positive effect of training contracts on profits, training may not be profitable unless some workers are overconfident.

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1 Introduction

Training by firms is a central means by which workers accumulate human capital. However, since at least [Pigou \(1912\)](#), economists have recognized that the provision of general training is subject to a “hold-up” problem. If workers cannot credibly commit to stay with firms after receiving training, firms will under-invest in training. The canonical solution developed by [Becker \(1964\)](#) is for workers to pay for training themselves, but this may not be feasible, for example, if workers are credit-constrained. Indeed, growing evidence shows that a significant portion of training is paid for by firms.¹ Hold-up may have important implications for the overall level of training in the economy. High worker turnover in the United States may make firms reluctant to train, thereby contributing to lower levels of training than in countries with lower turnover (e.g. [Blinder and Krueger, 1996](#)). Understanding what makes training profitable for firms may thus be important for optimal human capital policy.

To discourage workers from quitting after receiving training, firms often use training contracts. In these contracts, the firm pays for training, and in exchange workers must agree to stay with the firm for some period of time. If workers leave early, they must pay penalties. Training contracts of this form are used for many workers, including truckers, policemen, firefighters, nurses, pilots, securities brokers, and federal employees, to name a few, but have received limited attention from economists.² How do training contracts affect worker turnover, worker selection, and firm training? How do training contracts affect profits and welfare? While training contracts are legally permissible within some guidelines, some have argued that training contracts are exploitative and tantamount to a mild form of indentured servitude, and there have been recent legal challenges.³ How should training contracts be regulated?

To address these questions, I use rich data from the U.S. trucking industry where I document that training contracts are frequently used. The main data in the paper are from a leading trucking firm, referred to as Firm A, at which there is plausibly exogenous contractual variation. At Firm A,

¹See e.g. [Barron et al. \(1999\)](#), [Acemoglu and Pischke \(1999a\)](#), and [Cappelli \(2004\)](#) for evidence that firms often pay for training, both nominally and in terms of incidence. U.S. firms appear to spend less on training than firms in other countries ([Lynch, 1993](#); [Brunello and Medio, 2001](#)), but training expenditures are still substantial. For example, on tuition reimbursement alone, it is estimated that U.S. firms spent \$10 billion in 2003 ([Manchester, 2009](#)). There are many reasons besides credit constraints that firms will pay for training, including labor market frictions, information asymmetries, and screening benefits ([Acemoglu and Pischke, 1999a](#)). Further discussion of the firm-sponsored training literature is given in Section 2.

²See the law articles by [Kraus \(1993, 2008\)](#) for these examples, as well as a review of legal issues surrounding training contracts. Other workers with training contracts include metalworkers, mechanics, salesmen, paramedics, electricians, accountants, teachers, flight attendants, bank workers, repairmen, firm-sponsored MBAs, and social workers. In economics, there is a small related literature on firms providing tuition reimbursement, which I discuss in Section 2. In most of these studies, tuition reimbursement is provided as a benefit and not as part of a contract where the worker is obligated to stay for a length of time.

³Arguments that training contracts are exploitative have been made, for example, in the context of police officers. As of 2006, the City of Los Angeles used a training contract requiring new officers to stay five years after receiving training. [McGreevy \(2006\)](#) quotes a non-L.A. police official arguing that the contracts constitute indentured servitude. The City of Oakland also requires police officers to stay five years after receiving training. In November 2010, an Oakland police officer sued to challenge her contract, with the case decided by the 9th Circuit of the U.S. Court of Appeals. See *Gordon v. Oakland*. In *Heder v. City of Two Rivers*, a firefighter argued his training contract constituted “involuntary servitude.”

training was initially provided free of charge with no contractual obligations. In the early 2000s, a newly promoted manager suggested the idea of using a training contract, arguing it could improve retention, as well as help recover training costs. A training contract was created that required trained workers to stay 12 months or pay a penalty if they left early. The contract was phased into different training schools at different times, depending on how fast the contract was approved for use in different states. Around five years later, the company unrolled an 18-month contract with a higher initial quit penalty that decreased with tenure. I exploit the staggered timing of these two contract changes to estimate the impact of training contracts. The 12-month and 18-month contracts reduced quitting by 18 and 11 percent, respectively, relative to a situation with no training contract. The effects appear to be primarily driven by incentives instead of selection.

In Jovanovic's (1979) seminal theory of turnover, workers gradually learn about their productivity or job match, using their updated beliefs in deciding whether to quit. Thus, a big advantage of the Firm A data is that weekly panel data on worker subjective productivity forecasts are available for a large subset of drivers. Drivers are paid almost exclusively per mile driven (a piece rate), so beliefs about miles are highly consequential for how much drivers think they will earn. I analyze the belief data so as to better understand worker turnover in the presence of training contracts. Workers' beliefs about future productivity significantly predict quitting and future productivity. In addition, the data show that workers are substantially overconfident about their productivity, though there is significant heterogeneity. On average, workers' initial productivity beliefs exceed their productivity by roughly 25%. Overconfidence decreases over time, but persists throughout the two year panel.

Overconfidence raises important considerations for the efficacy and welfare consequences of training contracts. If workers are overconfident about their future earnings at the current job relative to the outside option, they will be more likely to sign up for training contracts and more likely to stay after training. This makes training more profitable for firms. Overconfidence may also be important for understanding whether training contracts are exploitative. Specifically, workers may overestimate how successful they will be at the job and end up owing penalties for training they would not have undertaken had they not been overconfident.⁴

To better understand observed behavior and to quantify these considerations, I develop a dynamic model of turnover and belief formation. In many empirical models of turnover, workers are assumed to know their future productivity at the firm. However, in my model, productivity is initially unknown and is instead gradually learned about over time as in Jovanovic (1979). Using weekly productivity realizations, workers form expectations of their future productivity and earnings, and use this to decide whether to quit. Although workers update their beliefs in response to new information, they may hold biased priors and/or update faster or slower than a Bayesian would, thereby nesting (a simplified version of) the Jovanovic model as a special case. The estimated structural model replicates several key features of the data including the quit-tenure curve, the productivity-tenure curve, and the

⁴The argument that contracts can be exploitative or unfair due to behavioral biases has been made in the legal literature, e.g. Kronman (1983), Eisenberg (1995), and Jolls and Sunstein (2006). Eisenberg (1995) argues that behavioral limitations constitute one of the major rationales for restricting the contracts people should be allowed to sign.

belief-tenure curve. Both overconfidence and learning are key. Without overconfidence, the model predicts too much early quitting and fails to rationalize the subjective belief data. Additionally, without learning, the model does not generate the inverted U-shaped quit hazard observed in the data, nor does it predict that observed overconfidence will decrease over time. Estimating the model using workers with the 12-month contract, I show that the model can predict reasonably well out of sample, helping rationalize behavior under the no contract and 18-month contract regimes.

I use the estimates for counterfactual simulations. First, I show that the firm increased profits through its contractual changes, but decreased worker welfare. Second, I consider the counterfactual of reducing worker overconfidence. Eliminating the observed amount of overconfidence would moderately increase worker welfare, but would substantially decrease firm profits and worker retention. Profits would decrease by over \$7,000 per truck in the baseline case. Third, I analyze a government ban on training contracts. Firms are assumed to maximize profits subjects to workers' participation constraint. Because they believe it is unlikely they will want to quit, overconfident workers are willing to accept a large quit penalty in return for a small wage increase. Banning training contracts has the potential to improve welfare for overconfident workers and I find that a ban increases worker welfare by 4%. I also study optimal training contracts for firms, showing that as worker overconfidence is reduced, the optimal training contract becomes smaller.

While the results in my paper are specific to a particular industry, there are several reasons why long-haul trucking provides an interesting setting for studying the effects of training contracts. First, training contracts are a common mechanism by which general training is provided for truckdrivers, a large occupation employing 3.2 million Americans.⁵ Second, and more importantly, trucking provides a natural setting for examining training contracts in the context of [Jovanovic's \(1979\)](#) model of turnover where workers gradually learn about their productivity. Unlike in many other industries, productivity in trucking (miles driven per week) is easily measurable, and is accurately recorded by firms given that it is used for determining worker payment. There is considerable variation in productivity across workers, but such differences are unlikely to be known *ex ante*. Third, trucking is an industry with high turnover, allowing for high-frequency retention analysis.

My study makes three contributions to the literature. First, I show that training contracts significantly reduce worker turnover, estimating the effects using plausibly exogenous intra-firm contractual variation. As discussed in the literature reviews by [Prendergast \(1999\)](#) and [Chiappori and Salanie \(2003\)](#), theory has often preceded measurement in economists' study of contracts. Firms' contractual choices are often difficult to observe, and contracts are unlikely to be randomly assigned across or within firms even when they are observable.⁶ While [Chiappori and Salanie \(2003\)](#) argue that natural experiments may help researchers circumvent such endogeneity problems in studying

⁵See Section 3 below for information on the extent of training contracts in trucking.

⁶For example, it may be imagined that firms with more serious retention problems may be more likely to adopt training contracts. A regression predicting retention may incorrectly show that training contracts have zero or even a negative effect on retention. Alternatively, it may be that only the most successful firms or firms providing the best training think to adopt training contracts, in which case a regression predicting retention will overstate the effect of training contracts. By looking at multiple plausibly exogenous contract changes *within different segments of a single firm over time*, I provide credible estimates of causal effects.

contracts, relatively few such studies exist. Second, I provide long-term high-frequency field evidence on overconfidence, the longest I am aware of in the literature, and quantify its welfare impacts for workers.⁷ To do so, I develop a structural learning model augmented with heterogeneous and potentially biased beliefs. I contribute to a small, but growing literature incorporating behavioral biases into structural models.⁸ Third, I demonstrate that worker overconfidence benefits firms by increasing the profitability of training. Counterfactual simulations suggest that biased beliefs are quantitatively important in facilitating training; even when firms use training contracts, training would not be profitable for firms unless workers are also overconfident. Just as firms may benefit from consumers having time-inconsistent preferences or biased beliefs,⁹ so too may firms benefit from their workers having biased beliefs.¹⁰

Whether it would be possible to reduce worker overconfidence is a separate question from what its impacts would be. I explore the feasibility of reducing overconfidence in a companion paper, [Hoffman \(2011b\)](#). In a field experiment with 254 workers at a different large trucking firm, I find that providing workers with information substantially reduces overconfidence, but that the effect decreases with time.

The paper proceeds as follows. Section 2 reviews the literature. Section 3 provides background on training contracts and trucking. Section 4 describes the data and analyzes the impact of the contractual changes. Section 5 analyzes the subjective belief data. Section 6 develops the dynamic model. Section 7 discusses estimation and identification. Section 8 provides structural results. Section 9 performs counterfactual simulations. Section 10 concludes.

2 Related Literature

My paper adds to a growing literature on firm-sponsored training, which is critically surveyed in [Acemoglu and Pischke \(1999a\)](#).¹¹ The closest part of the literature on firm-sponsored training to my paper is that on tuition reimbursement. Employer-provided tuition reimbursement programs are quite common in the U.S. For firms with more than 20 employees, estimates of the share offering tuition reimbursement have ranged from 47% ([Lynch and Black, 1998](#)) to 85% ([Cappelli, 2004](#)). In a recent sample of MBA students, [Manchester \(2011\)](#) found that 87% received tuition assistance, with 42% of those obligated to come back to the firm for 12 or more months after completing the MBA. [Manchester \(2009\)](#) shows that workers receiving non-binding tuition reimbursement are more likely

⁷For other longer term evidence of overconfidence, see [Massey et al. \(2011\)](#) who study overconfidence in football fans over the four months of the NFL football season.

⁸See also [Laibson et al. \(2007\)](#), [Conlin et al. \(2007\)](#), [Paserman \(2008\)](#), [Fang and Silverman \(2009\)](#), [Acland and Levy \(2011\)](#), [Bellemare and Shearer \(2011\)](#), [Crawford and Meng \(2011\)](#), [DellaVigna et al. \(2012\)](#), and [Grubb and Osborne \(2011\)](#).

⁹See e.g. [DellaVigna and Malmendier \(2004, 2006\)](#), [Eliaz and Spiegler \(2006\)](#), [Grubb \(2009\)](#), and [Ericson \(2010\)](#).

¹⁰The point that firms may benefit from worker biases is also made in the recent experiment by [Larkin and Leider \(2011\)](#).

¹¹A small sample of the recent literature on firm-sponsored training includes [Stevens \(1994\)](#), [Acemoglu \(1997\)](#), [Acemoglu and Pischke \(1998\)](#), [Acemoglu and Pischke \(1999b\)](#), [Parent \(1999\)](#), [Barron et al. \(1999\)](#), [Autor \(2001\)](#), [Buddin and Kapur \(2005\)](#), [Belzil et al. \(2009\)](#), [Lazear \(2009\)](#), and [Dustmann and Schoenberg \(forthcoming\)](#).

to stay with a firm. Other recent papers analyzing tuition assistance include [Balmaceda \(2005\)](#) and [Gicheva \(2009\)](#). For a recent theoretical paper on bonding and turnover, which includes analysis of training contracts, see [Peterson \(2010\)](#).

That people are overconfident has been referred to as “the most robust finding in the psychology of judgment” ([De Bondt and Thaler, 1995](#)), and is the subject of a vast literature in psychology and a growing literature in economics.¹² [Moore and Healy \(2008\)](#) provide an excellent review and discussion of the literature, and distinguish between three types of overconfidence: relative overconfidence or “overplacement” (thinking you are better than others), absolute overconfidence or “overestimation” (thinking you are better than you actually are), and excessive precision (thinking your beliefs are more precise than they actually are). This paper focuses on absolute overconfidence, that is, truckers thinking their productivity will be higher than it actually is, and I will refer to this hereafter simply as overconfidence. Overconfidence research has mostly focused on short-term behavior performing laboratory tasks, e.g. completing trivia games. This paper analyzes overconfidence using weekly data over two years on forecasts about individual productivity, an individually-important piece of information. I study how overconfidence affects turnover using reduced-form and structural approaches, and I also analyze structurally how contractual design is shaped by workers’ overconfidence.¹³

My paper contributes to a large literature in labor economics on learning. In learning models, agents acquire information about an unknown economic parameter. Learning has been used to analyze wage growth ([Harris and Holmstrom, 1982](#); [Schoenberg, 2007](#); [Kahn and Lange, 2011](#)), wage discrimination ([Altonji and Pierret, 2001](#)), and occupational choice (e.g. [Gibbons et al., 2005](#)). Several recent papers in labor economics analyze learning using a structural approach, including [Arcidiacono \(2004\)](#), [Papageorgiou \(2010\)](#), [Stange \(forthcoming\)](#), [Sanders \(2011\)](#), [James \(2011\)](#), and [Bojilov \(2011\)](#). Out of these, my paper is most closely related to [Bojilov \(2011\)](#), who analyzes worker learning about match quality using data on call center workers. My largest point of departure from these papers is that I allow for both generalized and non-rational learning. Specifically, I present the first paper on labor markets (to my knowledge) to estimate a learning model with biased beliefs. Structural learning models have also been applied fruitfully in non-labor contexts, including macroeconomics, industrial organization, and political economy. Two papers in industrial organization, [Goettler and Clay \(2010\)](#) and [Grubb and Osborne \(2011\)](#), estimate biased learning models of cellular phone service demand. A main difference in my paper is that belief biases are identified using high-frequency subjective belief data.¹⁴

¹²Recent papers on overconfidence in economics include [Burks et al. \(2010\)](#), [Eil and Rao \(2011\)](#), [Benoit and Dubra \(forthcoming\)](#), [Mobius et al. \(2010\)](#), [Ericson \(2011\)](#), [Grossman and Owens \(2010\)](#), [Charness et al. \(2010\)](#), [Hoffman \(2011a\)](#), and [Hoffman \(2011b\)](#).

¹³See [Oyer and Schaefer \(2005\)](#) and [Bergman and Jenter \(2007\)](#) for discussion of overconfidence and firms’ decisions to issue stock options. See [Sandroni and Squintani \(2007\)](#) for how overconfidence affects insurance markets. See [Spinnewjin \(2010\)](#) for how overconfidence affects optimal unemployment insurance.

¹⁴In [Goettler and Clay \(2010\)](#) and [Grubb and Osborne \(2011\)](#), biases are identified through contractual choices. There are advantages and disadvantages to using beliefs and contract choices to identify biases. An advantage of using contracts relative to using subjective beliefs is that economists are more trusting of “what people do” compared to “what people say.” A disadvantage of using contracts is that repeated sub-optimal *ex post* choices may reflect factors other than biased beliefs, including inertia or switching costs. Because of the richness of the belief data, I am able to estimate

Finally, my paper relates to a literature in economics analyzing data on subjective beliefs. Pioneering work by Charles Manski and colleagues argues that economic agents can meaningfully report their subjective beliefs, and that these beliefs can be useful for understanding economic behavior.¹⁵ A small number of papers have used subjective beliefs to estimate structural models. [Delavande \(2008\)](#) estimates a discrete choice model analyzing young women’s contraceptive choices. [van der Klaauw and Wolpin \(2008\)](#) use subjective belief data to analyze retirement decisions. [Erdem et al. \(2005\)](#) estimate a structural model of active learning (where agents choose how much information to acquire) about computer purchases using data on price expectations. [Wang \(2010\)](#) estimates a model of smoking with belief bias and subjective expectations data. [Pantano and Zheng \(2010\)](#) show how to use subjective expectations data to more flexibly estimate unobserved heterogeneity in structural models.

3 Training Contracts and Training in Trucking

3.1 Theoretical Preliminaries

Training contracts attempt to solve the hold-up problem in the provision of general training. Consider a credit-constrained worker employed at a given firm. A socially optimal training investment is available which raises the worker’s productivity by more than the cost of training. The training lasts a very short period of time so the cost of training cannot be deducted from worker wages, and training is general (not firm-specific). Becker’s solution is for the worker to pay for training himself, but this may be infeasible due to the credit constraint. This situation can potentially be remedied by having the worker take on a training contract. The firm will pay for training, after which the worker must stay with the firm for some period of time. A training contract helps the firm recover training costs when a worker quits and may also reduce quitting.

It is not obvious, however, that a training contract will affect quitting. Suppose that workers and firms have no private information and that bargaining is costless. Then, by the Coase Theorem, turnover will be efficient, that is, it will occur if and only if the sum of the worker’s and firm’s outside options exceeds the value of the match. Moreover, turnover will be unaffected by a training contract. In the Coasean framework, a training contract merely represents a “property right” held by firms over the quit decision and thus will have no effect on turnover.^{16,17}

heterogeneity in people’s belief biases, e.g. some people are well-calibrated, some are moderately overconfident, some are very overconfident, etc. This heterogeneity is important both for rationalizing the data and also for considering optimal policies, as the welfare consequences of different policies (particularly banning training contracts or debiasing) will differ depending on a person’s overconfidence.

¹⁵For an excellent discussion of the literature on subjective beliefs, see [Manski \(2004\)](#).

¹⁶To see why, consider the case where it is socially optimal for the worker to quit, but disadvantageous for the firm. Without a training contract, the worker will quit; the firm will try to “bribe” the worker to stay, but the maximum bribe the firm is willing to offer will still not be high enough to retain the worker. With the same situation and a training contract in place, the worker and firm will bargain such that (after negotiation) the worker will still quit. Whether the worker must bribe the firm to let him quit may be affected by the training contract, but the quitting outcome will not be.

¹⁷In a related application of the Coase Theorem, [Lazear \(1990\)](#) analyzes job security provisions in Europe, where firms are “fined” (e.g. they must pay severance pay) for firing workers. He shows theoretically how the Coase Theorem

In my context, however, it seems unlikely that the conditions of the Coase Theorem will hold. Workers likely have private information (about their taste for the job or their outside option) and renegotiating contracts with thousands of workers may be costly for a large firm like Firm A. In the Appendix, I present a model of training and turnover assuming workers have private information and assuming no renegotiation. I show that allowing for training contracts increases the profitability of training and reduces turnover.

One concern about training contracts is that they may harm workers if workers do not have accurate beliefs and/or if workers make bad decisions. If workers are overconfident about what their post-training ability will be relative to their outside option, they may be willing to take on a high-penalty training contract. In addition, after training, overconfidence may distort a worker's quitting decisions, making them stay longer with a firm than is rational. Though overconfidence may harm workers, it may benefit firms who use training contracts. As I show in the Appendix, overconfidence may make training more profitable for firms both by making it easier to get workers to sign training contracts and by making it easier to retain workers after training.¹⁸

3.2 Legal Issues Regarding Training Contracts

Courts in the U.S. and abroad have generally ruled that training contracts are legally permissible, arguing they serve the public good by promoting investment in worker training.¹⁹ Most training contracts have the following form. Training is provided at no cost in exchange for the worker agreeing to stay with the company for some period of time. The worker faces penalties if they leave early. Contracts of many lengths have been employed. In trucking, the duration of training contracts is often 6-24 months, whereas for police officers, contracts for five years are sometimes used (Kraus, 2008). Although I 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 cost 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 varied in how they have treated training contracts with large amounts owed.²⁰ 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.²¹

may fail to hold and shows empirically that job security provisions do indeed affect firm firing.

¹⁸In fact, I show in the Appendix that if overconfidence is not permanent, then overconfidence and training contracts are complementary. Overconfidence increases the probability of training when training contracts are allowed, but not if they are not allowed.

¹⁹This section draws primarily on the excellent review articles by Kraus (1993, 2008).

²⁰For example, *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 contract to be unenforceable. However, 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 salesman trainee did not fulfill three years of service, the court deemed the contract to be enforceable.

²¹See e.g. Judge Richard Easterbrook's opinion in *Heder v. City of Two Rivers*.

3.3 Background on the U.S. Trucking Industry

Trucking is one of America’s largest occupations, employing 3.2 million workers in 2008 ([Bureau of Labor Statistics, 2010](#)). Of these, around 25% work for for-hire motor carrier firms (i.e. “trucking firms”), with the remainder working for non-trucking firms that also employ truckdrivers (e.g. companies like Walmart and Safeway). This paper focuses on workers at trucking firms. The industry is usually divided into two segments, Less than Truckload and Truckload. Less than Truckload drivers deliver small to medium sized loads, usually make local deliveries, usually do not spend nights away from home, and have moderate rates of unionization. In contrast, truckload drivers deliver large loads across long distances, and have much lower rates of unionization.²² Truckload drivers are usually paid by the mile (a piece rate) ([Belzer, 2000](#)).²³ Within the truckload segment, around 10% of miles in 1992 were driven by drivers who own their own truck (owner-operators), with the remainder driven by drivers driving company-owned trucks (company drivers) ([Baker and Hubbard, 2004](#)). This paper focuses on company drivers in the Truckload segment. Turnover in the industry is high at over 100% annually and is highest among new drivers.²⁴

The main training for truckdrivers is training to obtain a commercial driver’s license (CDL). It usually consists of a combination of classroom lecture, simulator driving, and actual behind-the-wheel truck driving, and provides the skills and knowledge necessary to safely operate a large truck. Most new drivers take an official CDL training course, and in some states it is required by law ([Bureau of Labor Statistics, 2010](#)). CDL training can be obtained at truckdriving schools, which are run by trucking firms or run privately, or can be obtained at some community colleges. Training courses usually last 2-4 weeks, and are certified by the Professional Truck Driver Institute ([Bureau of Labor Statistics, 2010](#)), which requires courses to contain at least 148 hours of instruction, including at least 44 hours of time spent driving ([Professional Truck Driver Institute, 2010](#)).²⁵ The market price for CDL training at private training schools varies, but is often around several thousand dollars.

Truckdriver hours are legally restricted per the federal Hours-of-Service Regulations. Truckdrivers can work up to 60 hours per week.²⁶ Despite the hours restrictions, however, there is large variation in average miles across drivers, as well as significant week-to-week variation within drivers. Driver miles are influenced by many factors, including time management, trip planning, and driver speed.²⁷

²²In 2008, 16% of all truckdrivers and driver/sales workers were union members or covered by union contracts ([Bureau of Labor Statistics, 2010](#)).

²³For an analysis of productivity in trucking, see [Hubbard \(2003\)](#).

²⁴In the first quarter of 2008, the turnover rate at large carriers (those with more than \$300 million in revenue) was 103% and 80% for smaller Truckload carriers ([Suzuki et al., 2009](#)), where the turnover rate is defined as the number of workers who leave a company each year per 100 workers. The rate at large carriers has decreased in the 2008-2009 recession to 65%, but was at 130% in 2005 ([Roth, 2009](#)). For more general information on the trucking industry, see e.g. [Burks et al. \(2011\)](#).

²⁵A secondary form of training for truckdrivers is on-the-job driving training, where a new driver drives with a veteran driver sitting in the passenger seat. This type of training varies in length and formality between different firms, ranging from a few hours to several weeks. Though this training is also costly for firms, it is much less so than CDL training. I do not focus on this training, since training contracts are written to cover CDL training.

²⁶Drivers can alternatively work up to 70 hours over eight days. See <http://www.fmcsa.dot.gov/rules-regulations/topics/hos/index.htm>.

²⁷One important factor is whether drivers arrive to a location on-time. Drivers who arrive late may have to wait for

Factors such as weather, traffic, and variable loading/unloading time create substantial within-driver mileage variation. Thus, weekly miles, my measure of productivity, reflect both driver performance and factors that drivers do not control.

3.4 The Extent of Training Contracts in Trucking

To collect information on the extent of training contracts, I conducted phone interviews with the 20 largest dry-van and 10 largest refrigerated trucking companies in the U.S. I obtained the list of the largest trucking companies from [Transport Topics \(2009\)](#), a leading industry trade journal. I collected panel data on the type of training provided and on the training contracts used by each firm from 2001-2010. Interviews were conducted with someone familiar with the details of driver training, usually the director of human resources, the director of training, or a driver recruiter. Further information on the interviews is given in the Appendix.

Firm-sponsored training and training contracts are widespread in trucking. 16 of the 30 largest trucking companies report operating their own training school at some point from 2001-2010. When firms provided training at a CDL school, it was almost always provided under a training contract: Only two companies (including the company studied in this paper) sometimes provided CDL training without using a training contract. In addition, many companies offer tuition reimbursement programs, where drivers can receive their training elsewhere, and have the amount paid back over time by the company according to a contract. Only six companies never offered either firm-sponsored training or tuition reimbursement at some point from 2001-2010. Many companies report that they engage in firm-sponsored training because it is often difficult to find enough qualified drivers. At least four companies either stopped training new drivers or cut back significantly on training during 2008-2010 in the wake of the Great Recession. Larger firms appear to be more likely to train.²⁸

The form of training contracts varies across companies, 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.

4 Data and Reduced Form Analysis

4.1 Contract Changes

To examine the effects of training contracts, I make use of two large contract changes at Firm A, a leading U.S. trucking company. Firm A provides CDL training to thousands of new drivers at

their truck to be unloaded, which can be highly detrimental to weekly miles, given that the 60 hours per week is hours of working time, including both driving and non-driving.

²⁸In a regression of CDL training on log 2008 revenue, the coefficient on log 2008 revenue is 0.16 ($p = 0.06$).

several geographically dispersed training schools. Prior to 2001, all training was provided at no cost to the worker with no contractual obligation.

In late 2000, a newly promoted manager proposed the idea of implementing a training contract. According to the Director of Driver Training, management had not been previously aware of the possibility of using a training contract. The primary motivation for implementing a contract was to help increase retention, with a secondary motivation being to help recover costs. In order to implement the contracts, it was necessary in each state to have the contract certified by the state.²⁹ This certification process took different amounts of time in different states. The contract was approved quickly in several training schools and was in use by April 2002. At another training school, the contract was not approved until the end of 2002, and in a couple states the contracts were never used as the certification process dragged on indefinitely.³⁰ The penalty for leaving varied slightly by training school and was between \$3,500 and \$4,000. The contract lasted 12 months and the quit penalty was constant throughout the 12 months. The contract applied for both quits and fires.³¹

After several years of the 12-month contract, management began to discuss increasing the duration of the contract as well as changing its form. According to a Senior Vice President, the interest in changing the contract stemmed from a desire to retain new drivers for longer. Management decided to switch to an 18-month contract. The initial penalty for leaving would be higher, but would decrease gradually with a worker's tenure. Again, the contract was phased in gradually. Under the new 18-month contract, the amount owed was initially around \$5,000, and was reduced by \$62.50 for each week of service. Of the \$62.50 per week, \$50 was paid by the firm, and \$12.50 was deducted from the worker's pay check. After two years with the company, the driver would be returned his \$12.50 payments over 78 weeks in the form of a single bonus payment. Both the adoption of the 12-month and 18-month contracts were made without additional changes in the drivers' wage.³²

New drivers signed a written contract specifying the amount they would owe if they left within some period of time. No initial bond was posted. Upon early exit, drivers were contacted by the company to pay the amount due, either immediately or in monthly installments. If drivers did not pay promptly, they were referred to one of multiple collection agencies. Though comprehensive data on collection is not available, company records from late 2004 reveal that Firm A was collecting roughly 20 percent of the amount owed before referring accounts to collections. The collection agencies then collected an additional 5 to 10 percent.³³

²⁹It was explained to me that the training schools are considered private colleges, and training contracts are counted as a form of loan contract.

³⁰The Director of Driver Training believed that the differences in time for state approval were idiosyncracies of the state bureaucracy, and not related to the type of impact the contracts might have.

³¹According to several managers at Firm A, the reason why the contract also covered fires was to prevent workers who wanted to quit from trying to get fired. According to these managers, the firm did not intentionally fire workers to collect training penalties.

³²Firm A pays slightly different mileage rates depending on driver regions. It increased its overall pay schedule twice during the period for which I have data, once, in early 2004, and a second time, in late 2007.

³³A 25-30% collection rate may seem on face to be fairly low. However, collection efforts by Firm A appeared to be fairly strenuous. Drivers who did not pay received numerous strongly worded letters and phone calls from the company. For drivers who remained delinquent, credit agencies were notified.

4.2 Data

The data from Firm A are highly advantageous for an analysis of the impact of training contracts due to the large sample size and high frequency of observation. The data contain weekly miles and earnings for thousands of drivers from mid 2001 to 2009. I focus exclusively on new inexperienced drivers who are trained by Firm A. Drivers are paid by the mile, with small payments for other tasks.³⁴ For each driver, there is also basic demographic information.³⁵

Very detailed data are available for a subset of 895 new drivers. These drivers were trained at one of the firm’s training schools in late 2005 and 2006. I refer to drivers in this group as the data subset, and I focus much of the structural analysis on this group. Data on these drivers were collected in [Burks et al. \(2009\)](#). Subjective belief data about next week’s productivity are available only for drivers in the data subset.³⁶

Table 1 provides summary statistics for the data. The top panel shows summary statistics under the different contractual regimes: No contract, 12-month contract, and the 18-month gradual contract. Many driver characteristics before and after the contract change look fairly similar. There are some statistically significant differences in characteristics across the regimes, but some of these reflect inter-school demographic differences (since contracts were in place in different schools for different lengths of time). The lower panel provides summary statistics for the data subset. Drivers’ average schooling is slightly over 12 years. The median driver is male, white, and 35 years old.³⁷ The drivers have very low average credit scores. Of the 88% of drivers with credit scores (12% of drivers do not have a sufficient credit history to have a credit score), the average credit score is 586 and the median credit score is 564. According to [CreditScoring.com](#), the median credit score for the U.S. general population is 723. While only 7% of the U.S. population have a credit score below 550, 43% of drivers have a credit score below 550.

4.3 Do Training Contracts Affect Quitting?

To analyze the effect of training contracts on quitting, I first plot survival curves under the different contractual regimes in Figure 1. Survival is significantly higher for both the 12-month and 18-month contracts relative to the no contract regime. Figure 2 compares the quitting hazards for the three

³⁴Drivers also receive small additional payments for non-miles related tasks such as going through customs, loading and unloading, scales weighing, working on trailers, and training other drivers. After one year, drivers are also eligible to receive a quarterly bonus. A small number of drivers are paid based on their activities or on salary instead of by the mile (e.g. drivers who work full time as driver trainers at the training schools).

³⁵I restrict my sample to drivers from 5 training schools, excluding 3 schools where the training provided differed and/or the precise contract change dates were not available.

³⁶Further information about the firm and the data is given in [Burks et al. \(2009\)](#), who show a strong relationship between cognitive skills and driver retention in the data subset. The number of 895 represents the drivers who successfully graduated from the training academy. From these 895 drivers, I drop any drivers who are ever seen working at non-piece rate trucking jobs where they are paid based on their activities or on salary (e.g. this drops drivers who ever go to work themselves as driver trainers at the training schools). This leaves a sample of 735 drivers. The structural analysis focuses on a sample of 699 drivers for whom one of several covariates is not missing.

³⁷Truckdrivers must be at least 21 years old to cross state lines in a truck ([Bureau of Labor Statistics, 2010](#)) and Firm A requires new drivers to be over 21.

contractual regimes. For drivers with the 12-month contract, the hazard decreases until the 52-week mark, where there is a large spike. There are also smaller bumps at the 52-week mark under the no contract and 18-month regimes.³⁸

To more closely quantify these effects, I estimate Cox proportional hazard models of quitting. Every week, a driver faces some risk of quitting, which is influenced by his characteristics, including whether or not he has a training contract:

$$\begin{aligned} \log(h_{it\tau cs}) &= \alpha_t + \beta_1 * 12MCONTRACT_{sc} + \beta_2 * 18MCONTRACT_{sc} \\ &+ \beta_3 * UNEMP_{s\tau} + \beta_4 \bar{y}_{it} + \gamma_\tau + \delta_c + \theta_s + X_i \lambda + \epsilon_{it\tau cs} \end{aligned} \quad (1)$$

where $h_{it\tau cs}$ is the quit hazard of driver i with t weeks of tenure in year τ who is part of cohort (year of hire) c who attended training school s ; $UNEMP_{s\tau}$ is the unemployment rate in state s at time τ ; \bar{y}_{it} is average productivity to date; α_t is a fixed effect for tenure t ; γ_τ is a time fixed effect; δ_c is a fixed effect for year of hire c ; θ_s is a school fixed effect; X_i are individual covariates; and $\epsilon_{it\tau cs}$ is an error. The coefficients of greatest interest are β_1 and β_2 , representing the effects of the two contracts on the quit hazard. By including school fixed effects, I help rule out the possibility that the effects are simply due to the contracts being used for long periods of time at schools with high retention. By including time fixed effects, I help rule out the issue that factors other than the contracts changed over time. These results are shown in Table 2. As seen in column 1, the coefficients on the 12-month and 18-month contract variables are -0.18 and -0.11, respectively. That is, the 12-month and 18-month contract decrease the probability of quitting by roughly 18 and 11 percent.³⁹ A percentage point increase in state unemployment is estimated to reduce quitting by 5.6%. Thus, the estimated impact of the 12-month (18-month) training contracts is similar to a 3 (2) percentage point increase in the unemployment rate. When average productivity and demographics are controlled for, the estimates of β_1 and β_2 remain similar or become larger. The interaction effects in Table 2 reveal at what tenure levels the training contracts are reducing quitting. The effect of the 12-month contract is felt during the first 12 months (as expected), whereas the effect of the 18-month contract is experienced most in weeks 53-78.

To examine further how the effects of the contracts varied with tenure, I ran OLS regressions of quitting on interactions of the contracts with tenure blocks:

³⁸Managers at Firm A suggested that the bumps under the no contract and 18-month regimes may result from workers being able to say that they worked for a full year at Firm A when applying for other jobs.

³⁹Throughout the reduced form analysis on the full Firm A dataset, standard errors are clustered at the training school class (school-week of hire) level. Doing so allows for arbitrary correlation of the error within workers of the same training school class.

$$\begin{aligned}
q_{it\tau cs} = & \sum_{r=1}^8 \beta_{1r} * 12MCONTRACT_{sc} * TENUREQUARTER_r \\
& + \sum_{r=1}^8 \beta_{2r} * 18MCONTRACT_{sc} * TENUREQUARTER_r \\
& + \beta_3 * UNEMP_{s\tau} + \beta_4 \bar{y}_{it} + \eta_t + \gamma_\tau + \delta_c + \theta_s + X_i \lambda + \epsilon_{it\tau cs}
\end{aligned} \tag{2}$$

where $TENUREQUARTER_r$ is a dummy for a driver being in the r th quarter of tenure (e.g. $r = 1$ means the driver has 1 – 13 weeks of tenure, $r = 2$ means the driver has 14 – 26 weeks of tenure, etc.). The estimates are shown in Figure 3. Under the 12-month contract, quitting is significantly lower (relative to no contract) in the 4th quarter (weeks 39-52), but is significantly higher (relative to no contract) in the 5th quarter (weeks 53-65). This postponement of quitting behavior likely reflects the sharp decline in the quitting penalty at one year. Under the 18-month contract, quitting is significantly lower (relative to no contract) in quarters 4-6, but then increases after that.

4.3.1 Event Study Analysis

Another approach to identification is to analyze new driver quit patterns before and after the contract changes using an event study methodology. For the transition from no contract to the 12-month contract, I analyze quitting in weeks 46-52. Under the 12-month contract, drivers may optimally wait until their year is up before quitting, whereas the same incentive is not present for drivers with no contract. For the transition from the 12-month to the 18-month contract, I analyze quitting in weeks 53-78. Those under the 12-month contract may have waited for the year to expire, whereas these weeks are still under contract for the 18-month contract. For the transition from the 12-month to the 18-month contract, the event study can be represented with the following regression equation:

$$Quit5378_{ics} = \alpha_s + \beta_c + \sum_{j=\underline{T}}^{\bar{T}} \theta_j D_{sc}^j + X_i \lambda + \epsilon_{ics} \tag{3}$$

where $Quit5378_{ics}$ is a dummy for whether worker i quits in weeks 53-78 (conditional on having stayed through week 52), α_s and β_c are school and cohort fixed effects, and ϵ_{ics} is an error. D_{sc}^j is a dummy for whether those in quarter of hire c at training school s are j periods from the introduction of the 18-month contract; formally, $D_{sc}^j = \mathbf{1}(c - e_s = j)$, where e_s is the quarter when school s adopted the 18-month contract. To avoid collinearity, I normalize $\theta_{-1} = 0$. For the switch from no contract to the 12-month (18-month) contracts, I assume that $\underline{T} = -3$ and $\bar{T} = 9$ ($\underline{T} = -7$ and $\bar{T} = 4$). Further, I “bin up” the end points by including dummies for the event time being less than \underline{T} or greater than \bar{T} .⁴⁰ Results are shown in Figure 4. For the transition to the 12-month contract, the probability of quitting during weeks 46 to 52 drops by roughly 5 percentage points. Likewise, for the transition to the 18-month contract, there is a large decrease in the probability of quitting in

⁴⁰Note that I restrict the estimation sample in the event study to drivers who eventually exit the company.

months 53-78 occurring at the time of the contract change. Specifically, the probability of quitting decreases by roughly 20 percentage points. The average probability of quitting in the months 13-18, conditional on staying for one year, is about 53%. Thus, this effect represents a sizeable decrease in quitting in response to the contract.

4.3.2 Threats to Identification

Worker Sorting into Schools. One potential confound to identifying the impact of training contracts on quitting would be worker sorting into schools. For example, a worker who believed he had a high chance of quitting might prefer to attend a training school that did not have a training contract. This is unlikely to be an issue at Firm A because drivers almost always attend the training facility closest to their home. Specifically, 83% of drivers live in a state where at least 90% of Firm A drivers attended the same training school.⁴¹

Endogenous Contract Changes. The estimation above assumes that the implementation of training contracts is orthogonal to unobserved factors affecting quitting. However, if training contracts were implemented in areas expected to have higher quitting, then I will underestimate the effect of training contracts on quitting. Alternatively, if it was easier to implement the training contracts where future quitting was expected to be lower, then I will overestimate the effect. Managers at Firm A thought this was unlikely to be a concern, believing the timing of training contract approval to be idiosyncratic, likely reflecting differences in the speed of state bureaucracy. In the data, implementation of the training contracts is not predicted by state unemployment rates (which may be correlated with unobserved factors affect quitting), as I show in the Web Appendix.

Tenure-Varying Contract Enforcement. Under the 12-month contract, a worker who quit after 51 weeks was technically responsible for the same penalty as a worker quitting just a few weeks after training. Could it have been that training contracts were enforced differently depending on worker tenure? Such a possibility does not threaten identification of the overall impact of the training contracts on quitting, but may affect the interpretation of impacts by tenure. Although disaggregated data on contract enforcement are not available, managers at Firm A said training contracts were enforced generally irrespective of worker tenure.⁴²

4.4 Incentives or Selection?

A decrease in quitting from training contract penalties may result through incentive and/or selection effects. If a worker is penalized for quitting, he may become less likely to quit, that is, training contracts may have an incentive effect. However, adding a training contract for quitting may also affect the selection of workers who choose to work at the firm. If workers are fined for quitting early,

⁴¹Of the drivers that live in a state where less than 90% of the drivers attended the same training school, more than half live in one state approximately equidistant from two training schools. Excluding drivers from this state, 94% of drivers live in a state where at least 90% of the drivers attended the same training school.

⁴²A training manager at Firm A raised one exception. Contracts were sometimes not enforced if workers were fired after very short tenures. However, other than that, I was told that contract enforcement did not depend on a driver's tenure.

low productivity workers or workers with a low taste for trucking may be less likely to sign up. Thus, training contracts may have a selection effect on worker quitting, drawing in higher ability workers or workers with a higher taste for the work.

One informal test for selection is to examine whether training contracts affect the rate of firing. If training contracts deterred low-quality drivers from working at Firm A, one would expect a decrease in the rate of firing. In the Web Appendix, I analyze the effect of the contracts on firing rates. None of the coefficients are statistically different from zero. There is thus no evidence that the contracts affected the rate of firing, though the estimates are less precise than those on quitting.

A second test is to examine whether selection occurred on various observable characteristics. The most obvious characteristic to examine is productivity: Did adding a training contract lead more productive workers to begin working at the firm? As seen in Table 3, there is limited evidence that training contracts led to more productive workers selecting to work at the firm. One can also test for selection by looking at whether workers with other characteristics (potentially correlated with a worker's taste for the job or tendency to quit) are more likely to choose to work for the firm once training contracts are in place. There is evidence that the contracts may have affected selection on several characteristics (whether the driver is Hispanic, whether the driver smokes, and whether the driver applied online), but this evidence is not conclusive.

My third test of selection aims at testing whether there was selection on unobserved taste for trucking. Suppose that there are two types of drivers: "Good drivers," who are productive and who have a high taste for trucking, and "Bad drivers," who are less productive and have a low taste for trucking. The training contract would induce positive selection if it caused a greater share of new workers at the firm to be "Good drivers." If the contracts caused positive selection, controlling for productivity should reduce the estimated magnitude of the coefficients on the contract variables in quit hazard models. However, as can be seen in column 3 of Table 2, the contract dummy coefficients are roughly the same or become even larger in magnitude, once productivity is controlled for. Thus, the above test provides no evidence to support the idea that the contract induced positive selection.⁴³

These tests provide support for some selection due to the training contracts, but the effects seem somewhat limited. Overall, the evidence suggests that the effect of the training contracts on quitting operated primarily through incentives. Given the strong evidence of selection effects of contracts in other personnel settings (e.g. Lazear, 2000), why does positive selection here appear to be small? One possibility is that workers lack private information about their productivity when signing up for the job. Long-haul trucking is very different from most other jobs and it may be very difficult to predict how good one will be at it.⁴⁴ Another possibility is that for some reason the contract

⁴³This test is inspired by the test for selection in Lazear (2000), who tests for selection by analyzing whether the coefficient on the piece-rate dummy changes once individual fixed effects are added. He finds that the coefficient on the contract dummy falls by half, leading him to conclude that selection explains half the treatment effect of the contract. My test is significantly more indirect, given that I cannot observe the same individual under multiple contractual regimes.

⁴⁴In my structural model, I will make the assumption that workers and firms do not have private information about the worker's productivity before he starts work.

may not have been salient to drivers when they signed up for the job.⁴⁵ A third possibility may be that selection is multidimensional.⁴⁶ Ultimately, however, I am unable to distinguish between these different possibilities.

4.5 Worker Learning

In the next section, I model the quitting decision as a product of worker learning. Workers are initially uncertain about how productive they will be as truckdrivers and gain information about their underlying productivity through weekly productivity signals. Workers who learn that they are less productive become more likely to quit. A testable implication of learning about productivity is that quitting should reflect selection on average productivity. Specifically, at every point in time, workers who are less productive should be more likely to quit. Figure 5 confirms this by comparing the average earnings per week of drivers who quit that week versus drivers who make it to that week and do not quit. Quitting drivers receive lower average earnings in prior weeks than non-quitting drivers. Selection on productivity is examined with controls in Table 2. As can be seen, an increase in past average productivity significantly reduces the hazard of quitting.

5 Worker Beliefs

Worker productivity beliefs are key in theories of turnover. I examine whether incorporating subjective beliefs can help better predict productivity and turnover under training contracts. Every week, drivers in the data subset were asked to predict their miles in the following week, being sent the below question over the Qualcomm message system in their truck:

About how many paid miles do you expect to run during your next pay week?

Drivers responded by typing in their answer. I interpret this question as asking drivers their beliefs about their average number of miles next week. Individual driver responses and participation were never shared with the company and this was emphasized to drivers. No incentives were used to incentivize accurate belief responses, though drivers were given \$5 each week for completing the survey.⁴⁷ The average response rate across all drivers and weeks to the weekly beliefs question is 21%. Of the 699 drivers whom I focus on in the data subsample, 61% respond to at least one survey about mileage beliefs.⁴⁸

⁴⁵This seems unlikely to be the case, as a discussion of training contracts was a mandatory part of interviews at Firm A.

⁴⁶Multidimensional selection has been observed, for example, in health insurance contracts (Finkelstein and McGarry, 2006). In my setting, workers could potentially be selecting both on productivity and their level of overconfidence. If less productive workers are also more likely to be overconfident about their productivity, then low and high productivity workers may have similar productivity beliefs and may not be differentially selected by different contracts.

⁴⁷At a different large trucking firm, I elicited miles expectations while randomizing whether or not drivers were given financial incentives for accurate beliefs (Hoffman, 2011b). Incentives ranged from up to \$0, \$10, or \$50 per week for accurate guessing. I find no evidence that overconfidence is reduced by using incentives. Other field studies using incentives for belief elicitation include Grisley and Kellogg (1983) and Nelson and Bessler (1989).

⁴⁸Women and minority drivers are less likely to respond to the survey, whereas workers with higher average productivity and older drivers are more likely to respond. Within a given driver, response is higher in weeks when the driver

In Table 4, I examine whether subjective productivity beliefs help predict productivity over and beyond other predictors. Specifically, I consider regressions of the form:

$$y_{i,t} = \alpha + \beta b_{i,t-1} + \gamma \bar{y}_{i,t-1} + X_i \delta + \epsilon_{i,t} \quad (4)$$

where $y_{i,t}$ is driver i 's productivity in his t^{th} week with the company, $b_{i,t-1}$ is his previous week's belief about his productivity in the next week, $\bar{y}_{i,t-1}$ is lagged average productivity to date, X_i includes controls, and $\epsilon_{i,t}$ is an error. Column 1 estimates with only lagged beliefs on the right-hand side; the estimated β is roughly 0.2. Once controls such as average productivity to date are included, the coefficient dips to roughly 0.06, as more productive people tend to have higher beliefs. The predictive power of productivity beliefs holds *within person* as well, that is, after individual fixed effects are included. Overall, worker subjective beliefs have informational content, but the effect is much less than one for one. The relatively low coefficients likely reflect attenuation bias due to measurement error in subjective beliefs.

Table 5 reports the impact of productivity beliefs in a proportional hazards model of quitting

$$\log(h_{i,t}) = \alpha + \beta b_{i,t-1} + \gamma \bar{y}_{i,t} + X_i \delta + \epsilon_{i,t}, \quad (5)$$

where $h_{i,t}$ is the quit hazard. Average earnings to date, $\bar{y}_{i,t}$ is a sufficient statistic for beliefs about productivity in a basic normal learning model. Thus, the above regression asks whether driver quitting decisions reflect the additional information drivers have about their productivity. The results show that they do. A 100 mile increase in subjective miles predicts a 6 percent decrease in the probability a worker quits. The true effects are probably higher, with observed estimates biased downward due to measurement error. The effect is robust to the inclusion of different controls including average productivity to date. The coefficient on beliefs does not change very much across the different specifications. Compared to a standard setup where workers hold the same beliefs given their productivity signals and observed characteristics, it appears here that workers' heterogeneous subjective beliefs are in fact predictive of quitting.

Besides whether subjective beliefs are predictive, another basic question is whether or not they are well-calibrated. Figure 6 analyzes productivity and productivity beliefs by tenure. Productivity and productivity beliefs are collapsed by week of tenure and then smoothed using a local polynomial regression. As can be seen, workers on average consistently believe they will be more productive than they actually are. Beliefs exceed actual productivity both in terms of means and medians.⁴⁹ Workers are initially overconfident by roughly 500 miles per week, or approximately 25% of their productivity. This percentage declines over time, though it is quite persistent. Even after 100 weeks

is more productive. Later on in the structural analysis, I perform a robustness check where I use Inverse Probability Weighting (Wooldridge, 2002) to address non-random response to the question.

⁴⁹I interpret the question "About how many paid miles do you expect to run during your next pay week?" as asking drivers for their mean expected miles next week. Another possible interpretation is that it is asking drivers for their median expected miles next week. In the data subset, mean and median miles are almost identical (the median of worker miles per week is 1% less than the mean miles per week). Thus, whether workers reported their mean or median expected miles seems unlikely to matter for the structural estimation.

of signals, workers are still overconfident by around 150 miles per week.⁵⁰

The results mask substantial heterogeneity and variability across and within drivers. Though on average workers are overconfident in almost every week, weeks where drive predictions are higher than next week’s actual miles constitute only 65% of the data, whereas weeks where driver prediction are lower than next week’s actual miles constitute 35% of the data. Thus, it is not the case that each individual driver is overpredicting his miles every week. Drivers also differ substantially in the share of the time they overpredict their miles, and in the level of their over- or under-prediction. Evidence on heterogeneity is plotted in Figure 7, which displays driver-level average mile beliefs, actual miles, and the difference between the two. Many drivers are moderately overconfident, but there are also many drivers who are well-calibrated, as well as some drivers who are very overconfident.

For overconfidence to reduce worker quitting in theory, the worker must be more overconfident about his current job earnings than his outside option. While this assumption is very difficult to test, I provide some suggestive evidence that the assumption is satisfied. Drivers in the data subset were asked what their earnings would have been had they not started work with Firm A.⁵¹ I compare drivers’ response to this question to what “similar-looking” people earned in the March 2006 Current Population Survey (CPS). Figure 8 shows the comparison. As can be seen, workers do not believe that they appear to earn significantly more than people like them in the CPS. That is, the perceived outside option workers would had earned had they not gone through training does not appear to be significantly higher than what people like them might be earning.

6 The Model

I develop a dynamic model of quitting and belief formation where workers learn about their productivity over time. The model is a discrete time extension of the model in Jovanovic (1979) allowing for biased beliefs. The goal of the model is to provide a framework for understanding the facts presented above and to serve as a basis for subsequent counterfactual analysis.

A worker decides each week whether to quit his job. The problem is an optimal stopping problem; once he quits, he cannot return. Quitting is the only decision to make – in particular, there is no effort decision. The worker is paid per mile driven. Workers have different underlying productivities, but productivity is initially unknown, both to the worker and the firm. Each week’s miles provides a noisy signal about the worker’s true productivity. The worker is forward-looking, basing his quit decision on his subjective expectation of his future productivity and the option-value of staying on with the firm to learn about his productivity. However, workers may be subject to belief biases.

⁵⁰An important issue not addressed in Figure 6 is differential attrition, as low-productivity workers are more likely to quit. In the Web Appendix, I reproduce the figure restricting the sample to workers who stay with the firm at least 75 weeks and the overall pattern is similar (though the sample is smaller). In estimating the level of overconfidence in the structural model, the attrition process is explicitly modeled.

⁵¹The exact wording was “Which range best describes the annual earnings you would normally have expected from your usual jobs (regular and part-time together), if you had not started driver training with [Firm A], and your usual jobs had continued without interruption?” The eight income ranges were \$0 – \$10,000, \$10,000 – \$20,000, and so on until \$70,000+.

The worker’s priors need not be accurate; he may believe that trucking will be very lucrative or he may hold more reasonable beliefs. Further, as new productivity information arrives, he may over- or underweight his prior relative to pure Bayesian updating. Biases in priors will diminish as new information comes in, but not necessarily quickly. In addition to heterogeneity in productivity and beliefs, workers also differ in their taste for their job or career. Quitting decisions will reflect a driver’s underlying taste (e.g. how much one dislikes being away from home) as well as idiosyncratic shocks (e.g. having a fight with the boss).⁵²

In the model below, both the piece rate and training contracts are taken as given; both are endogenized later in Section 9 when I consider optimal contract design for the firm.⁵³

6.1 Model Setup

Workers have baseline productivity η , which is distributed $N(\eta_0, \sigma_0^2)$. Workers are paid by a piece rate, w_t , that depends on their tenure.⁵⁴ Workers know the piece rate-tenure profile, but believe that this profile will not be changed by the company at some future date. The time horizon is infinite and given in weeks 1, 2, A worker’s weekly miles, y_t , are distributed $N(a(t) + \eta, \sigma_y^2)$, and weekly earnings are thus $Y_t = w_t y_t$. $a(t)$ represents a known learn-by-doing process, which I specify below. The worker also has an outside option r_t . 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, \dots, y_{t-1} , but not their current week miles, y_t . Workers are assumed to be risk-neutral and to have a discount factor given by δ .⁵⁵

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

$$V_t(\mathbf{x}_t) = \max_{d_t, d_{t+1}, \dots} E_t \left(\sum_{s=t}^{\infty} \delta^{t-s} u_t(d_s, \mathbf{x}_s) \mid d_t, \mathbf{x}_t \right). \quad (6)$$

where \mathbf{x}_t is the vector of state variables at time t . \mathbf{x}_t includes past miles, y_1, \dots, y_{t-1} , and is described further below. The maximization problem can also be written as the following Bellman Equation:

$$V_t(\mathbf{x}_t) = \max_{d_t} E_t (u_t(d_t, \mathbf{x}_t) + \delta V_{t+1}(\mathbf{x}_{t+1}) \mid d_t, \mathbf{x}_t).$$

I assume that there is unobserved heterogeneity in how much drivers enjoy working in trucking. A worker’s non-pecuniary taste for working in trucking is denoted by α . The per-period utility from

⁵²I assume that workers’ tastes for the job are realized immediately instead of learned about over time. That learning occurs only over productivity may be unrealistic; there is also likely learning about other aspects of job fit, as trucking is different from most other jobs (e.g. away from home for weeks at a time, working by oneself, etc.). Investigating turnover with multiple dimensions of learning is an important subject for future research.

⁵³In addition, I abstract away from the firm’s ability to fire workers.

⁵⁴This is the standard pay system for the U.S. trucking industry. For example, a trucker who does not own his own truck may receive 30 cents per mile.

⁵⁵Risk neutrality is assumed in many dynamic learning models, e.g. Crawford and Shum (2005), Nagypal (2007), Stange (forthcoming), and Goettler and Clay (2010), though not in all (for examples with risk aversion, see the recent survey paper by Ching et al. (2011)). Coscelli and Shum (2004) show that risk parameters are not identified in certain classes of learning models.

staying is assumed to be given as the sum of utility from earnings, the taste for trucking, and an idiosyncratic shock:

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

where ε_t^S is an iid idiosyncratic error unobserved to the econometrician (but observed by the worker) with an Extreme Value-Type 1 distribution and scale parameter τ . I assume that the unobserved heterogeneity is drawn from a mass-point distribution (Heckman and Singer, 1984).⁵⁶

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 being the penalty for quitting at tenure t . The utility from quitting can be written as:

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

where ε_t^Q is an iid unobserved idiosyncratic error with the same distribution as ε_t^S . Note that the fraction $\frac{r_t}{1-\delta}$ includes a time subscript, expressing that a worker's outside option may depend on his tenure at quitting (though the reservation wage is assumed to be constant after some distant time T). It is useful to define the two choice-specific value functions. Let

$$\begin{aligned} V_t^S &\equiv E_t(u_t(1, \mathbf{x}_t) + \delta V_t(\mathbf{x}_{t+1}) | 1, \mathbf{x}_t) \\ V_t^Q &\equiv E_t(u_t(0, \mathbf{x}_t) + \delta V_t(\mathbf{x}_{t+1}) | 0, \mathbf{x}_t) \end{aligned}$$

be the value functions for staying and quitting, respectively. Using the continuation values, and the above expressions for $u_t(1, \mathbf{x}_t)$ and $u_t(0, \mathbf{x}_t)$, the choice-specific value functions can be written as:

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

and the Bellman Equation can be re-written as

$$V_t(\mathbf{x}_t) = \max_{d_t \in \{0,1\}} \left(V_t^S(\mathbf{x}_t), V_t^Q(\mathbf{x}_t) \right).$$

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:

⁵⁶I have also performed estimation allowing the unobserved heterogeneity to be normally distributed.

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

Belief Formation. In a standard normal learning model, a worker's beliefs in period t about his productivity are given by:

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

This expression is a weighted sum of the agent's prior and his average productivity signals. As t increases, the agent will eventually shift all the weight to the \bar{y}_{t-1} term over the η_0 term. I augment the standard learning model in two ways. First, I allow for agents to be overconfident. Instead of believing that their productivity η is drawn from a distribution $N(\eta_0, \sigma_0^2)$, agents believe that the productivity is drawn from a distribution $N(\eta_0 + \eta_b, \sigma_0^2)$. Second, I allow for agents to have a perception of signal noise that may be different from the true signal noise in the population. Specifically, workers may perceive the standard deviation of weekly productivity signals to be $\widetilde{\sigma}_y$ instead of σ_y . With these two assumption, an agent's subjective expectation of his productivity, which I denote by E^b (where b stands for belief) is:

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

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

I allow that workers' reported subjective beliefs include some measurement error. The rationale is that accurately reporting one's beliefs about productivity may be unusual or unfamiliar for a worker. I assume that reported beliefs equal subjective beliefs plus a normally distributed error. Specifically, the reported subjective belief of driver i in his t^{th} week of tenure, b_{it} , is distributed:

$$b_{it} \sim N\left(E^b(y_{it}|y_{i1}, \dots, y_{it-1}), \sigma_b^2\right)$$

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

1. Workers form beliefs b_t given past earnings y_1, y_2, \dots, 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 over time with the function $a(t)$. I assume that $a(t) = a_1 * \Lambda(a_2 t)$ where $\Lambda(x) = \frac{e(x)}{1+e(x)}$ is the logit function and t is worker tenure in weeks.⁵⁷ Learning by doing depends only on tenure; thus, the speed of learning does not depend on the number of miles driven or on the ability of the driver. Workers fully anticipate the path of $a(t)$.

In addition, I account for skill accumulation immediately following CDL training. At Firm A and other trucking firms, truckdrivers who have just completed their CDL training often spend several weeks driving with an experienced driver riding along. At Firm A, this process lasts 4 to 6 weeks. During this time, drivers receive a flat rate of roughly \$375 per week and their productivity is not recorded in the payroll data. I thus assume that drivers do not begin learning from their earnings realizations until after 5 weeks. I also account for the fact that drivers who quit during this initial period of driving along a senior driver may lack some skills required to be a productive truckdriver. Specifically, I assume the reservation wage over time is given as follows:

$$\begin{aligned} r_t &= r - \frac{6-t}{5} s_0 \text{ for } t \leq 5 \\ r_t &= r \text{ for } t > 5 \end{aligned}$$

With this specification, r is fixed using outside data and s_0 , the value of skills gained while working with a senior driver, is a parameter to estimate.⁵⁸

State Variables and Observed Heterogeneity. The state variables consist of past earnings, a vector of observed time-invariant individual characteristics, the piece rate, the training contract, taste heterogeneity, and a person's level of overconfidence: $\mathbf{x}_t = (y_1, \dots, y_{t-1}, X, w_t, k_t, \alpha, \eta_b)$, where X is a vector of observable additional characteristics. Differences across people are accounted for by allowing for heterogeneity in taste for the job and in overconfidence. I have also allowed workers' taste and beliefs to depend on observable characteristics.

Solving the Model. To solve the model, I first solve for the asymptotic value functions (after all learning has taken place) using value function iteration. With the asymptotic value functions in hand, backward recursion can then be applied to solve the dynamic programming problem. At the time T , the probability of staying, given the state variable, is:

⁵⁷The logit 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.

⁵⁸I have also estimated allowing for skill accumulation to continue as driver tenure increases. Specifically, I assume that $r_t = r + \theta_1 \Lambda(\theta_2 t)$, where θ_1 and θ_2 are parameters to estimate.

$$\begin{aligned}
Pr(STAY_T|\mathbf{x}_T) &= Pr(V_T^S > V_T^Q | 1, \dots, y_{T-1}, X, w_t, k_t, \alpha, \eta_b) \\
&= Pr(\alpha + X\bar{\alpha} + E^b(w_T y_T | y_1, \dots, y_{T-1}) + \delta E(V(\mathbf{x})|\mathbf{x}_T) + \epsilon_T^S > -k_T + \frac{r}{1-\delta} + \epsilon_T^Q) \\
&= \Lambda \left(\frac{\alpha + X\bar{\alpha} + w_T E^b(y_T | y_1, \dots, y_{T-1}) + \delta E(V(\mathbf{x})|\mathbf{x}_T) + k_T - \frac{r}{1-\delta}}{\tau} \right)
\end{aligned}$$

where $\Lambda(x) = \frac{e(x)}{1+e(x)}$ is the logit function. To evaluate this probability, it is necessary to calculate $E^b(y_T | y_1, \dots, y_{T-1})$ and $E(V(\mathbf{x})|\mathbf{x}_T)$. This expectation depends on y_1, \dots, y_{T-1} , which would imply that the state space has dimensionality of order K^{T-1} when y_t is discretized with K values. The key to avoiding a very high dimensional problem is that, in a normal learning model, and in the generalized learning model I consider, the worker's expectation of future productivity depends only on the average of all past productivity realizations. That is, since $E^b(y_t | y_1, \dots, y_{t-1}) = \frac{\widehat{\sigma}_y^2}{(t-1)\widehat{\sigma}_0^2 + \widehat{\sigma}_y^2}(\eta_0 + \eta_b) + \frac{(t-1)\widehat{\sigma}_0^2}{(t-1)\widehat{\sigma}_0^2 + \widehat{\sigma}_y^2} \bar{y}_{t-1}$, the *average of his past productivity is a sufficient statistic for the entire sequence* y_1, \dots, y_{t-1} (DeGroot, 1970). I show how to calculate $E(V(\mathbf{x})|\mathbf{x}_T)$ in the Appendix.

For a general period t , the probability of staying is given by:

$$\begin{aligned}
Pr(STAY_t|\mathbf{x}_t) &= Pr(V_t^S > V_t^Q | \mathbf{x}_t) \\
&= Pr(\alpha + X\bar{\alpha} + w_t E^b(y_t | y_1, \dots, y_{t-1}) + \epsilon_t^S + \delta E(V_{t+1}(\mathbf{x}_{t+1})|\mathbf{x}_t) > -k_t + \frac{r}{1-\delta} + \epsilon_t^Q) \\
&= \Lambda \left(\frac{\alpha + X\bar{\alpha} + w_t E(y_t | y_1, \dots, y_{t-1}) + \delta E(V_{t+1}(\mathbf{x}_{t+1})|\mathbf{x}_t) + k_t - \frac{r}{1-\delta}}{\tau} \right)
\end{aligned}$$

Calculating $E(V_{t+1}(\mathbf{x}_{t+1})|\mathbf{x}_t)$ requires integrating expectations both of future earnings and future idiosyncratic shocks, and is done formally in the Appendix.

Exogenous Separations. In some specifications, I also allow for exogenous separations, that is, a probability that the worker-firm match will be destroyed.

6.2 Discussion of Model Assumptions

Outside of how workers form beliefs, most assumptions in the model are relatively standard. While worker learning is allowed to be non-standard, deviations such as overconfident priors will be determined by the data. The strongest assumption in the model is that workers are not overconfident about the outside option despite potentially being overconfident about their ability in trucking. Some evidence supporting the assumption was presented in Figure 8. However, the assumption is not required for overconfidence to have some effect on the profitability of training. As I show in the Appendix, firm profitability will be higher if there is some differential overconfidence, that is, the worker's perception of his current job income is more responsive to his productivity beliefs than his outside option. To the extent that workers are also overconfident about their outside option, this will attenuate the importance of overconfidence for firm profitability.

How reasonable is it to think that overconfidence affects the current job earnings more than the outside option? Suppose that the outside option is a non-trucking job. While current earnings are proportional to ability in trucking, most jobs in the U.S. do not pay piece rates. Thus, even if workers are overconfident about their productivity at their outside option, it is unclear how much this affects workers' perceptions of their earnings at their outside option.⁵⁹ Suppose now that the outside option is another trucking job. Insofar as drivers select the job at which they believe their ability will be the highest, they will be differentially overconfident about their ability at the current job relative to the outside option.⁶⁰

7 Structural Estimation

7.1 Estimation

The model is estimated using maximum likelihood. Let $L_i = L(d_{i1}, \dots, d_{it}, y_{i1}, \dots, y_{it}, b_{i1}, \dots, b_{it})$ be the likelihood of driver i for an observed sequence of quitting decisions, earnings realizations, and subjective beliefs. The likelihood can be expanded as follows:

$$\begin{aligned} L_i &= \int L(d_{i1}, \dots, d_{it}, y_{i1}, \dots, y_{it}, b_{i1}, \dots, b_{it} | \alpha, \eta_b) f(\alpha, \eta_b) d\alpha d\eta_b \\ &= \left(\prod_{s=1}^t L(y_{is} | y_{i1}, \dots, y_{is-1}) \right) \left[\int \prod_{s=1}^t L(d_{is} | y_{i1}, \dots, y_{is-1}, \alpha, \eta_b) \prod_{s=1}^t L(b_{is} | y_{i1}, \dots, y_{is-1}, \eta_b) f(\alpha, \eta_b) d\alpha d\eta_b \right] \\ &\equiv L_i^2 \int L_i^1(\alpha, \eta_b) L_i^3(\eta_b) f(\alpha, \eta_b) d\alpha d\eta_b \end{aligned}$$

$L_i^1(\alpha, \eta_b)$ is defined as the contribution to the likelihood from quitting decisions; L_i^2 is the contribution to the likelihood from earnings realizations; and $L_i^3(\eta_b)$ is the contribution to the likelihood from subjective beliefs. That the likelihood can be decomposed in this way is shown formally in the Appendix. For a driver who quits in period t , $L_i^1(\alpha, \eta_b)$, L_i^2 , and $L_i^3(\eta_b)$ can be written as

⁵⁹Performance pay is used in only 37% of U.S. jobs, comprises a median of 4% of total pay across jobs, and is less common in blue-collar jobs than white-collar jobs (Lemieux et al., 2009). Of course, other pecuniary aspects of a job, e.g. the perceived probability of being promoted to a higher wage, may be affected by overconfidence.

⁶⁰The argument that self-selection can promote belief biases is made in Van den Steen (2004). In the case where the outside option is another trucking job, the assumption that the worker is more overconfident at the current wage than at his outside option may be testable. Assume that the worker's overconfidence is correlated across firms with different multiplicative values, $\eta_{b,f} = \theta_f * \theta_b$, where $\eta_{b,f}$ is a worker's belief bias at firm f . In the regressions of quitting on beliefs in Table 5, I showed that workers who have higher beliefs are less likely to quit.

$$\begin{aligned}
L_i^1(\alpha, \eta_b) &= \left(\prod_{s=t}^{t-1} \Pr(STAY_{is} | \mathbf{x}_{is}) \right) (1 - \Pr(STAY_{it} | \mathbf{x}_{is})) \\
L_i^2 &= f(y_{i1}) * \prod_{s=2}^t f(y_{is} | y_{i1}, \dots, y_{is-1}) \\
L_i^3(\eta_b) &= f(b_{i1}) * \prod_{s=2}^t f(b_{is} | y_{i1}, \dots, y_{is-1})
\end{aligned}$$

with

$$\begin{aligned}
f(y_{i1}) &\sim N(\eta_0, \sigma_0^2 + \sigma_y^2) \\
f(y_{is} | y_{i1}, \dots, y_{is-1}) &\sim N((1 - \gamma_{s-1}) \eta_0 + \gamma_{s-1} \bar{y}_{is-1}, \Omega_{s-1}) \text{ for } s > 1 \\
f(b_{i1}) &\sim N(\eta_0 + \eta_b, \sigma_b^2) \\
f(b_{is} | y_{i1}, \dots, y_{is-1}) &\sim N\left(\left(1 - \gamma_{s-1}^b\right) (\eta_0 + \eta_b) + \gamma_{s-1}^b \bar{y}_{is-1}, \sigma_b^2\right) \text{ for } s > 1
\end{aligned}$$

and where $\gamma_s = \frac{s\sigma_0^2}{s\sigma_0^2 + \sigma_y^2}$, $\Omega_s = \frac{\sigma_0^2\sigma_y^2}{s\sigma_0^2 + \sigma_y^2} + \sigma_y^2$, and $\gamma_s^b = \frac{s\sigma_0^2}{s\sigma_0^2 + \sigma_y^2}$. The overall likelihood is computed, first, by integrating over the unobserved heterogeneity for each individual's likelihood, and then by taking the product over all people. Since the unobserved heterogeneity is mass-point distributed, the integral becomes a sum.

$$\begin{aligned}
L &= \prod_i \int L_i^1(\alpha, \eta_b) L_i^2 L_i^3(\eta_b) f(\alpha, \eta_b) d\alpha d\eta_b \\
&= \prod_i \left(\int L_i^1(\alpha, \eta_b) L_i^3(\eta_b) f(\alpha, \eta_b) d\alpha d\eta_b \right) L_i^2. \\
\log(L) &= \sum_i \log \left(\sum_{\alpha, \eta_b} L_i^1(\alpha, \eta_b) L_i^3(\eta_b) f(\alpha, \eta_b) \right) + \sum_i \log(L_i^2)
\end{aligned}$$

7.2 Identification

I discuss which data features allow me to identify the model parameters.

Productivity and skill parameters. The productivity parameters σ_0 , σ_y , and η_0 are identified primarily by the productivity data. σ_0 reflects the degree of permanent productivity differences *across* individuals whereas σ_y reflects differences *within* individuals in productivity. The parameter η_0 reflects mean average ability of workers in the population. The skill gain parameter, s_0 , is identified based on turnover levels during the first five weeks when workers are driving with an experienced driver and receiving a flat wage instead of a piece rate.

Taste heterogeneity. The taste heterogeneity parameters are identified from persistent differences between individual quitting behavior and the predictions of the model. Suppose that the data

contained many low-productivity workers who nevertheless kept choosing not to quit. This would cause the model to estimate that there is a large amount of unobserved taste heterogeneity.

Belief parameters. The subjective expectations data are critical for identification of all the belief parameters. The standard deviation of beliefs, σ_b , is identified by how much subjective expectations differ from the mathematical expectation of future productivity. The greater the variation in subjective expectations from mathematical expectations (that is, the greater the measurement error in state beliefs), the greater is σ_b . The believed standard deviation of productivity shocks, $\widetilde{\sigma}_y$, determines the subjective speed of learning in the model. Because workers use this subjective speed of learning both to make quit decisions and to form subjective beliefs, the parameter is over-identified. The faster that agents begin to weight their productivity realizations to date in making their quit decisions, the smaller that $\widetilde{\sigma}_y$ will be. Likewise, the faster that agents’ initial overconfidence in subjective beliefs begins to disappear, the smaller that $\widetilde{\sigma}_y$ will be. The belief heterogeneity is identified from persistent differences across individuals regarding how their subjective beliefs compare to the model’s mathematical expectation of future productivity. Suppose that some workers persistently report productivity beliefs that are much larger than their actual productivity, whereas other workers are well-calibrated. This would lead to estimating a large amount of belief heterogeneity.

Other parameters. The scale parameter of the idiosyncratic shock, τ , is identified based off of how much quitting behavior in the data differs from that predicted by a model with individual unobserved heterogeneity, but not time-varying uncertainty.

7.3 Implementation

To solve the dynamic programming problem numerically, I discretize productivity into K values. In my baseline estimation, I let productivity range in increments of 100 from 100 to 4,000 miles per week, *i.e.* $K = 40$.⁶¹ Transitions between earnings states are given by:⁶²

$$\Pr(y_s^k | y_1, \dots, y_{s-1}) = \Phi \left(\frac{y_s^k + .5 * kstep - E(y_s^k | y_1, \dots, y_{s-1})}{\sqrt{\Omega_{s-1}}} \right) - \Phi \left(\frac{y_s^k - .5 * kstep - E(y_s^k | y_1, \dots, y_{s-1})}{\sqrt{\Omega_{s-1}}} \right)$$

where $kstep$ is the distance between earnings realizations.

The outside option, r , is taken to be the median full-time earnings from the 2006 March Current Population Survey of workers like the “median” driver (35-year old males with a high school degree), which is \$32,000 per year. I convert this to a weekly wage of \$640. The weekly discount factor, δ , is assumed rather than estimated. In my preferred specification, I take $\delta = 0.9957$, corresponding to an annual discount factor of 0.8.⁶³

⁶¹As a sensitivity check, I have also estimated with finer and coarser discretizations, as explored for example in Rust (1987). The results are qualitatively similar except when the grid is very coarse. I have also estimated using linear interpolation instead of discretization and the results are similar.

⁶²See Rust (1996) and Stange (forthcoming) for similar formulas.

⁶³I have experimented with a broad range of discount factors in sensitivity analysis. Model fit appears best for discount factors in this range, though it still is quite reasonable for those corresponding to annual discount factor of 0.90. An annual discount factor of 0.80 is “low,” but is comparable or higher than discount factors used or estimated

A few other points are worth noting. First, I assume that drivers act as if the contract is perfectly enforceable.⁶⁴ Second, I report results here without including covariates like education and age.⁶⁵ Third, the data contain a number of zero mile, zero earnings weeks for drivers. During these weeks, the driver is not working. These weeks do not count toward the earnings component of the likelihood, and average earnings to date (in terms of the quit decision) are given by the prior week’s average earnings to date.

8 Structural Results

Table 6 displays the main structural estimates. As a benchmark, column 1 provides estimates assuming no belief bias. Column 2 allows workers to have a mean bias in their productivity expectations, that is, to be over- or underconfident about their ability. Workers are estimated to have an initial belief bias of 589 miles. Given the estimated mean of the prior productivity distribution of 2,025 miles, workers are estimated to be overconfident by around 29%. One should note that the productivity parameters are also different from column 1 and more reasonable in size.⁶⁶ The believed standard deviation of productivity shocks is roughly 2.5 times higher than the actual standard deviation of productivity shocks. This implies that the rate at which agents update their quit-related productivity expectations and reported subjective productivity expectations is a fair amount slower than the rate predicted by the productivity data alone. Recall that the weight agents place on their signals relative to their prior is $\frac{t\sigma_0^2}{t\sigma_0^2 + \sigma_y^2}$. After 20 weeks, the worker will place weight 0.31 on his signals, whereas if $\widetilde{\sigma}_y = \sigma_y$, he would place weight 0.77 on his signals.

Column 3 allows for heterogeneity in people’s belief bias. There is again a considerable improvement in the log-likelihood. The data reveal the majority of people to be moderately overconfident and a small group of people to be severely overconfident. There is also significant heterogeneity in people’s taste / non-monetary preference for working in trucking. All three models suggest three types of workers: Workers with a strong distaste for working in trucking, workers with moderate distaste, and workers with a moderate positive taste. Given that workers are forced to be away from home for several weeks at a time, that many workers dislike this is unsurprising.

The fit of the model is assessed graphically in Figure 11. The quit hazard-tenure profile, the productivity-tenure profile, and the beliefs-tenure profile observed in the data are plotted using an

in other analyzing dynamic choices of blue-collar or low-income workers (e.g. Paserman, 2008; Fang and Silverman, 2009; Warner and Pleeter, 2001).

⁶⁴As described above, even though only a portion of the amount owed was collected, I assume that drivers act as if the utility cost of quitting is equivalent to the utility loss from paying the contract penalty. The firm was very firm with new drivers about its intention to collect money owed upon a quit. Combining this with the actual aggressiveness of the collection efforts, as well as the reporting of delinquency to credit agencies, this assumption may not be tremendously unrealistic. I have also considered robustness checks where drivers act as if the utility loss from quitting is only a portion of the contract penalty.

⁶⁵I have estimated models including covariates as described above. However, including covariates has little effect on model fit and on the estimates of the other parameters.

⁶⁶For example, the mean of the prior productivity distribution is 2,025 miles per week, down roughly 20% from 2,468 miles per week in column 1. In column 1, the prior productivity distribution needs to explain the earnings data. But it also needs to explain the quitting and subjective beliefs data, which “pulls” the estimate substantially upward.

Epanechnikov kernel. Predicted quitting behavior is plotted by simulating the careers of 40,000 drivers. The model appears to match several patterns in the data. The hazard of quitting is initially increasing in both the model and the data. In the model, this is due to learning about productivity. When workers are uncertain about their productivity, they face an incentive to wait and see how productive they will be before deciding to quit. There is a large spike in quitting after 52 weeks as predicted by the model, the time at which drivers come off the 12-month contract. Learning also helps rationalize the gradually decreasing beliefs-tenure profile, though the fit is imperfect.

To further assess model fit, I can compare the observed number of drivers quitting (O_t) with the number predicted from the model (E_t) using a chi-squared test.⁶⁷ The chi-squared statistic for the model-predicted quit behavior is given by $\sum_t \frac{(E_t - O_t)^2}{E_t}$. Statistical inference is conducted using T degrees of freedom, where T is the maximum number of weeks a driver is observed. For column 1, the chi-squared statistic is 504.7684, whereas for columns 2 and 3, the chi-squared statistics are 216.1135 and 202.9855. Thus, although the data reject model 3 ($p = 1.6856e - 007$), the fit in terms of turnover is a considerable improvement over models without belief bias or with no belief heterogeneity. This occurs even though the belief bias parameters are simultaneously fitting both the belief data and turnover data.

Table 7 takes the baseline model and adds learning by doing and logit skill accumulation. The fit is better in all three specifications than in Table 6. Many of the parameters are qualitatively similar to before, but there are some differences. In column two, the mean prior bias is larger than before, estimated at 722 miles. The estimated taste heterogeneity is also somewhat different. Further results with learning by doing are given in the Web Appendix where instead of allowing for gradual skill acquisition, the models estimated allow for an exogenous probability of match separation after one year. The fit is inferior to that in Table 7, with lower log-likelihoods.

Robustness. I conduct a number of robustness checks of my main findings. I vary the discount factor, the number of mass points, the maximum allowed subjective belief, and the maximum time during which learning occurs. Results are in the Web Appendix. Comparing log-likelihoods under the assumed annualized discount factor of 0.80 with a fully myopic alternative ($\delta = 0$), the data soundly reject the myopic model ($p = 0.00$ in a likelihood ratio test). The model fit is slightly better for an annualized discount factor of 0.80 than 0.90 or 0.95, but the difference is not statistically significant. To account for the potential impact of differential response to the subjective belief questions, I perform a robustness check using Inverse Probability Weighting (Wooldridge, 2002). In the first stage, I fit a probit model of whether a driver responds to the survey as a function of time-invariant observables. I then use the inverse of the predicted values to weight each driver's contribution to the likelihood. Results are shown in the Web Appendix and are quite similar to the unweighted estimates.

⁶⁷Chi-squared tests are often used to assess the fit of dynamic models, e.g. Keane and Wolpin (1997) and Card and Hyslop (2005). As noted in Card and Hyslop (2005), it is more correct to think of the calculated chi-squared statistic as an informal measure of fit, since the predicted numbers are created from the same data being used for the observed cell entries.

Out-of-Sample Fit. A more demanding task of the model is to see whether it can predict well out-of-sample. The model is estimated using workers facing the 12-month contract, as this is the only data for which subjective beliefs at Firm A were collected. It is natural to ask whether the model can be simulated to predict behavior under the no contract and 18-month contract regimes. As I show in the Web Appendix, the model can predict the basic shape of the no contract and 18-month contract conditions, but the fit is imperfect.

9 Counterfactual Simulations

The section uses the structural estimates to assess the quantitative importance of training contracts and biased beliefs, as well as to analyze potential firm or government policies.

9.1 Profits and Welfare Under the Three Contracts

I first assess how different training contracts affect profits and welfare by simulating worker behavior under the three observed training contracts. I use two measures of firm profits: profits per worker and profits per truck.⁶⁸ Average profits per worker is defined as average profits brought in from a worker during his time with the company. Implicit in such a formulation is that when a worker quits, he is not replaced.

$$\begin{aligned}\pi(k) &= \text{Trucking Profits} + \text{Training Contract Penalties} - \text{Training Costs} \\ &= \sum_{t=1}^{\infty} \delta^{t-1} (1 - Q_t) ((P - w_t - mc)y_t - FC) + \sum_{t=1}^{\infty} \delta^{t-1} \theta k_t q_t - TC\end{aligned}\tag{9}$$

where q_t is a dummy for quitting in week t , $Q_t = \sum_{s=1}^t q_s$ is a whether a driver has quit in the first t weeks, y_t is a driver's productivity, P_t is the price the firm charges for one mile of shipment, mc is the non-wage marginal cost per mile (i.e. truck wear and gas costs), θ is the share of the training contract penalty collected by the firm, FC is fixed costs per week (i.e. support for the drivers and the opportunity cost of the truck), and TC is training cost per worker. I assume values for P , mc , θ , FC , and TC based on consultation with Firm A.⁶⁹

Profits can also be defined in terms of profits per truck. In this formulation, when a worker quits, he is replaced by the company the next period at some cost, which I set equal to the cost of the training. The formula for profits per truck is:

⁶⁸See [Bojilov \(2011\)](#) for similar profit formulas in a different context.

⁶⁹Specifically, I assume that $P = \$1.80$ per mile, $mc = \$1.20$ per mile, $\theta = 0.3$, $FC = \$475$ per week, and $TC = \$2,500$. It should be noted that even within Firm A there is variation in P and MC depending on the shipment and the driving conditions. The price per mile charged by Firm A to a shipper may depend on the type of commodity being hauled and on whether it is driven by team drivers (two drivers sharing a truck) who will deliver the good more quickly than solo drivers. In addition, workers may have different marginal costs depending on how they use the equipment. Incorporating such heterogeneity, however, is beyond the scope of this paper.

$$\pi = \sum_{t=1}^{\infty} \delta^{t-1} [(1 - Q_t)((P - w_t - mc)y_t - FC) + Q_t(-TC + \theta k_t + \pi)] \quad (10)$$

which can be re-arranged to yield

$$\pi = \frac{\sum_{t=1}^{\infty} \delta^{t-1} [(1 - Q_t)((P - w_t - mc)y_t - FC) + Q_t(-TC + \theta k_t)]}{1 - \sum_{t=1}^{\infty} \delta^{t-1} Q_t} \quad (11)$$

Since workers have biased beliefs, average actual (experienced) utility will differ from a worker’s expected utility. Worker welfare is measured using experienced utility by summing earnings, taste for trucking, and idiosyncratic shocks. I simulate 3,000 workers for up to 1,300 weeks each. As seen in Table 8, both measures of profits are higher under the 12-month contract than no contract, and higher under the 18-month contract than the 12-month contract. These results suggest that Firm A increased profits through its contractual changes, though also lowered worker welfare.

9.2 Debiasing: Reducing Worker Overconfidence

Workers exhibit overconfidence and overconfidence improves the fit of the structural model. To examine quantitatively how overconfidence affects quitting behavior, worker welfare, firm profits, and firms’ contractual choices, a natural counterfactual is to eliminate overconfidence, which I refer to as debiasing.

Before describing the counterfactual, it is worth considering whether reducing people’s overconfidence is feasible at all. Psychologists have long been interested in whether overconfidence and other behavioral biases can be eliminated, focusing primarily on laboratory settings.⁷⁰ In Hoffman (2011b), I show using a field experiment at another trucking firm that informing workers about other workers’ overconfidence can reduce confidence. Alternatively, overconfidence might be reduced if workers are informed about the distribution of productivity or if they receive individual-level feedback about their productivity and productivity forecasts.⁷¹ To the extent that debiasing is feasible, the counterfactual can be viewed not only as quantifying overconfidence, but also as a potential public policy experiment, e.g. a government information campaign that reduced overconfidence.

To examine the effects of debiasing, I simulate the structural model with the overconfidence mass points reduced. In addition to a full elimination of overconfidence, I also simulate a reduction of overconfidence by one half, recognizing that debiasing may be incomplete in practice. Results can

⁷⁰Fischhoff (1982) provides an excellent early summary of the literature. Many papers provide support for the feasibility of laboratory debiasing (e.g. Arkes et al., 1987; Lau and Coiera, 2009), but many also do not (e.g. Sanna et al., 2002; Fleisig, 2011).

⁷¹Outside the psychology literature, legal scholars have also taken an interest in debiasing, e.g. Jolls and Sunstein (2006). In addition to discussing information as a form of debiasing, Jolls and Sunstein (2006) also discuss how legal institutions may reduce behavioral biases. For example, one rationale for having an outside member of a corporate board is that they may be less prone to overoptimism about company performance than inside members.

be seen in Table 9. I find that the intervention substantially reduces worker retention; when workers are overconfident, they become much more likely to quit because they no longer unrealistically foresee themselves as being highly productive in the future. This also raises worker welfare since worker quitting decisions become less distorted by overconfidence. In addition, debiasing significantly reduces profits per worker and profits per truck. Because workers are quitting earlier, the firm has less time to make profits on a given worker, lowering profits per worker. Higher turnover from debiasing also means the firm must spend more on training costs to train new drivers.

Comparison Counterfactual: Reveal Ability to Worker After Training. To illustrate the importance of learning, I consider a counterfactual where learning is “turned off.” That is, I examine what happens if worker ability is revealed to workers immediately after training. In addition to eliminating uncertainty about ability, such a counterfactual eliminates all overconfidence since workers do not rely on their potentially biased priors to infer their ability. As seen in Table 9, revealing ability reduces retention at 20 weeks below that of 100% debiasing since many workers would quit immediately after discovering that they had low ability. The counterfactual also raises worker welfare and firm profits compared to 100% debiasing due to better allocation; productive workers become more likely to stay with Firm A and unproductive workers become more likely to leave. However, compared to the baseline, firm profits are substantially lower. Thus, it appears that firms benefit and workers lose because ability is gradually revealed in this market; if ability were revealed immediately, overconfidence would disappear, which as argued above, is bad for firms.

9.3 Debiasing with Optimal Contractual Responses

In the above counterfactuals, I take firms’ training contracts as fixed. However, in reality, firms might adjust their training contracts in response to debiasing. When workers’ overconfidence is reduced, workers will become more likely to quit after receiving training, and firms may wish to change the quitting penalties in response. In addition, if workers are debiased before they sign up for training, it may be more difficult to get them to sign a training contract.

In the optimal contracting problem I consider, the firm sets the piece rate and quit penalty for every week $1, 2, \dots, \infty$. Rather than solving analytically, I attack the problem using computational methods.⁷² Even with modern computational tools, I need to simplify the problem. The training contract penalty is assumed to be a flat level \bar{k} for weeks 1-52 and zero thereafter. The wage is restricted to be a scale-factor \bar{w} times the actual wage profile. The firm solves the problem:

$$\max_{\bar{k}, \bar{w}} E\pi(\bar{k}, \bar{w}) \text{ s.t. } E^b V(\bar{k}, \bar{w}) \geq \bar{u} \quad (12)$$

where $E\pi(\bar{k}, \bar{w})$ is the firm’s expected profit per worker and $E^b V(\bar{k}, \bar{w})$ is the worker’s perceived expected utility under \bar{k} and \bar{w} . \bar{u} is the minimum utility level at which the worker will sign the training contract. Since worker perceived welfare is strictly decreasing in quit penalties in increasing

⁷²Several other papers use computational methods to analyze optimal contracts in rich contracting environments. For example, [Armstrong et al. \(2010\)](#) computationally analyze optimal compensation contracts with both moral hazard and adverse selection.

in the piece rate, the problem is condensed to a one-dimensional optimization problem. The firm chooses training contract penalties and piece rate schedules lying along an indifference curve.

I perform the analysis with \bar{u} equal to the perceived utility a worker would have gotten in each of the counterfactuals in Table 9. Estimates are shown in Table 10. Column 1 of Table 10 reports the optimal contract in the baseline situation, before any debiasing has occurred. The optimal contract involves a higher quit penalty and higher wage than that observed in practice. When overconfidence or learning are removed, the optimal quit penalties decrease. This occurs because overconfident workers believe it is unlikely they will quit and they are thus willing to accept a high quit penalty for a small wage increase.⁷³ Other aspects of the counterfactuals are similar to before. Debiasing decreases worker retention and firm profits, but increases worker welfare. Thus, the qualitative conclusions of the counterfactuals are unchanged when firms optimally set contracts compared to counterfactuals when contracts are fixed. In fact, the effects of debiasing appear to be amplified when contracts are optimally set, as it is “cheaper” for firms to satisfy participation constraints when workers are overconfident.⁷⁴

9.4 Banning Training Contracts

If workers have accurate beliefs about their expected productivity, then restricting the type of contracts workers and firms are allowed to sign seems unlikely to be welfare-enhancing. However, if workers are overconfident, it might be possible that they are taking on contracts that are lowering their welfare. In this case, worker welfare may be higher when firms are restricted from using training contracts. Courts could, for example, decide that training contracts should be unenforceable.

I model a ban in training contracts as a restriction on the firm’s optimization problem. Instead of (12), the firm solves the restricted problem:

$$\max_{\bar{w}} E\pi(\bar{k} = 0, \bar{w}) \text{ s.t. } E^b V(\bar{k} = 0, \bar{w}) \geq \bar{u} \quad (13)$$

Results are shown in the last two columns of Table 10. Worker welfare is 3.7% higher when training contracts are banned compared to when the firm optimally sets training contracts unrestricted. I also examine a combined policy of banning training contracts and 50% debiasing. Worker welfare is 2.7% higher under this counterfactual compared to 50% debiasing when firms optimally set training contracts. Note that if workers were fully well-calibrated, banning training contracts would have no effect since firms are optimally choosing to set $k = 0$. The value of using training contracts for a profit-maximizing firm appears to be linked to workers having biased beliefs.⁷⁵

⁷³In addition, higher piece rates are more appealing to workers who are more overconfident.

⁷⁴In these counterfactuals, I have let \bar{u} vary by counterfactual to equal what workers would get in perceived expected utility as in the case with no contractual response. This implies that when overconfidence is reduced, workers’ perceived outside option goes down as well. An alternative approach is to use the same \bar{u} in each counterfactual. Results are in the Web Appendix. Optimal profits are often lower than in Table 10 because as workers become debiased, their perceived expected utility goes down, and they require either a lower quit penalty or higher wage to have as high perceived utility as before. However, the other qualitative conclusions remain the same.

⁷⁵The analysis here assumes that firm-sponsored training would continue if training contracts were banned. It is possible, however, that banning contracts would make some firms no longer willing to train. In the Web Appendix, I

Robustness: Competition. I have studied optimal training contracts and banning training contracts for the case of a single monopsonistic firm. While the trucking industry as a whole is closer to perfect competition than monopsony, analyzing one firm may be a reasonable assumption for the market for firm-sponsored training. However, it is worth examining how competition would affect my conclusions. Under perfect competition, the impact of banning training contracts on worker welfare is more ambiguous than before. Although overconfident workers benefit by not taking on high quit penalties, they may be harmed since firms may need to substantially decrease wages to reach zero profits. The positive relationship between optimal quit penalties and overconfidence will remain under perfect competition since more overconfident workers dislike high quit penalties and like higher piece rates more than non-overconfident workers.⁷⁶

10 Conclusion

The question of how firms profitably train despite the potential for hold-up is a critical one both for economic theory and for policy. This paper explores the joint role of training contracts and biased beliefs in alleviating hold-up.

Using plausibly exogenous contractual variation, I show that implementing a training contract reduced quitting by 10 to 20 percent, an effect equivalent to a 2-4 percentage point increase in the driver's home state unemployment rate. I find only limited evidence of positive worker selection induced by training contracts, suggesting the effects operated through incentives instead of selection. Data on workers' subjective productivity beliefs predict actual quitting and productivity, but also indicate a significant and persistent pattern of overconfidence whereby workers believe they will achieve higher miles than they actually attain. To understand key patterns in the quits and beliefs data, I structurally estimate a quitting model with learning and overconfidence. I show that both training contracts and overconfidence are critical for the profitability of training. If training contracts were banned or overconfidence eliminated, firm profits from training would fall substantially, sometimes from positive to negative.

My results are specific to one industry, so it is worth considering to what extent the conclusions may generalize. Training contracts are used in many jobs, both other blue-collar jobs (e.g. mechanics, electricians, and metalworkers) and high-skill jobs (e.g. pilots, accountants, and securities brokers). Future work should examine whether the impacts of training contracts in these jobs appear to be similar. Is worker overconfidence relevant for firm training in other industries? The piece rate compensation system in trucking makes overconfidence easy to measure and consequential for expected

modify the counterfactual so that banning training contracts means that firms stop providing training. New truckers who received training from private schools would continue to get trained that way, but truckers receiving firm-sponsored training (the ones I study in this paper) could no longer enter the industry. This counterfactual reduces worker welfare, as might be expected. However, the impacts vary substantially by worker overconfidence. In my baseline model with two types of overconfidence, welfare for very overconfident workers actually increases whereas welfare for moderately overconfident workers decreases. Since the quitting decisions of very overconfident workers are strongly distorted, they are actually better off just receiving their outside option and not getting trained.

⁷⁶In current work, I am repeating the simulations for the case of perfect competition.

earnings. Even in jobs without piece rates, though, if the jobs people choose are the ones where they are most overconfident, differential overconfidence will also be present, thereby making workers less likely to quit. While I focus on firm training, overconfidence may also be relevant for other types of human capital investment, e.g. going to college, or for occupational choice in general.⁷⁷

To reach the above conclusions, a number of simplifying assumptions were made. I focused only on the quitting decision of workers without modeling the firing decision of firms.⁷⁸ In addition, I study optimal contract choice by one firm instead of considering firms offering competing training contracts. Finally, I analyze optimal contract design when the firm chooses a single contract instead of allowing the firm to offer a menu of training contracts.

Worker overconfidence and learning may be important for many aspects of optimal job design and compensation. For example, when firms can choose to pay flat wages or piece rates, paying a piece rate may be appealing if workers are overconfident since overconfident workers perceive they may earn more than they actually will ([Larkin and Leider, 2011](#)). Future work should analyze the equilibrium interplay between worker behavior and firms' contractual choices, both for training contracts and other types of contracts.

⁷⁷See [Stinebrickner and Stinebrickner \(2011\)](#) for evidence that college students are initially overconfident about their likely performance in college. There has been recent discussion, particularly related to law schools, that students may be overly optimistic about their future job prospects when taking on student loans, e.g. [Segal \(2011\)](#) and [Goodwin \(2011\)](#).

⁷⁸Although firing is about five times less common than quitting in the data, future work may wish to consider the game played between workers and firms where workers may quit and firms may fire.

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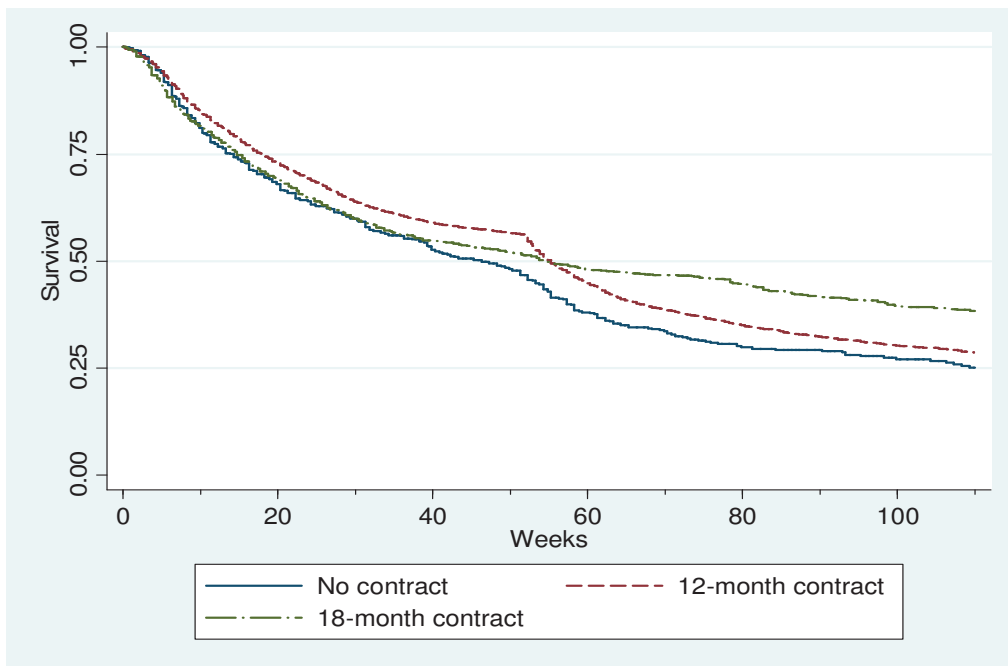
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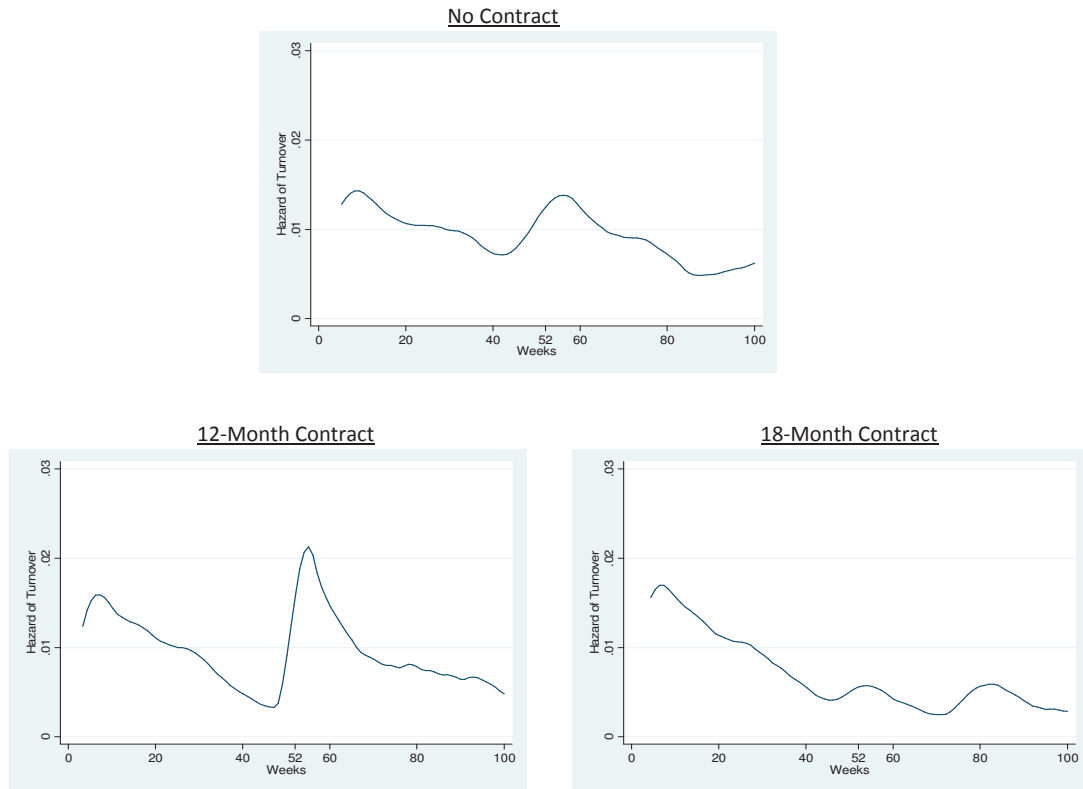
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Figure 1: Effect of Training Contracts on Driver Retention



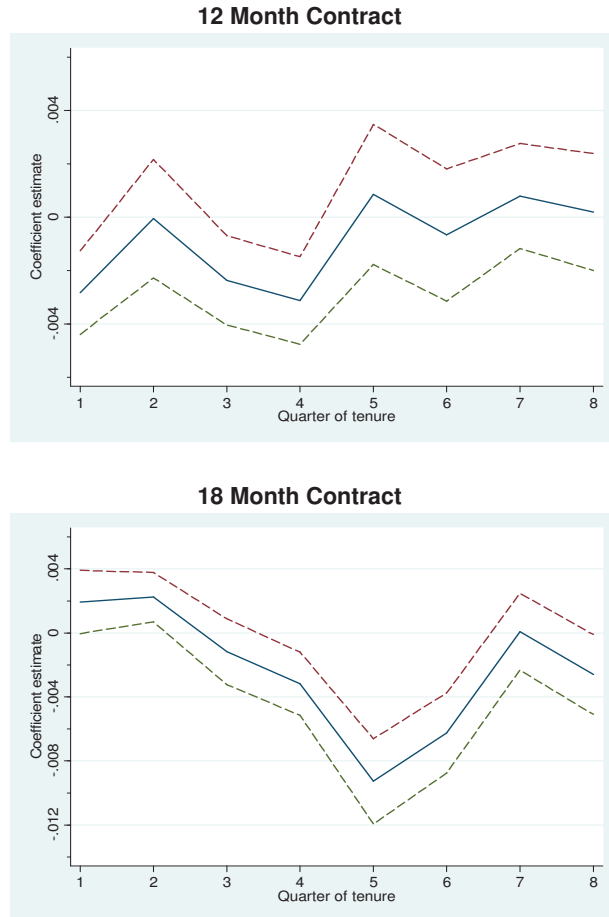
Notes: This graph plots the share of drivers surviving at any week under the 3 contractual regimes, using new system drivers starting at Firm A between 2001 and 2009. The figure is a Kaplan-Meier survival curve, and focuses only on exits by quitting (fires are treated as censored). Wilcoxon test for equality of three curves: $p < 0.01$. Wilcoxon test for equality of No contract and 12m contract regimes: $p < 0.01$. Wilcoxon test for equality of 12m contract and 18m contract regimes: $p < 0.01$.

Figure 2: Training Contracts and the Hazard of Quitting



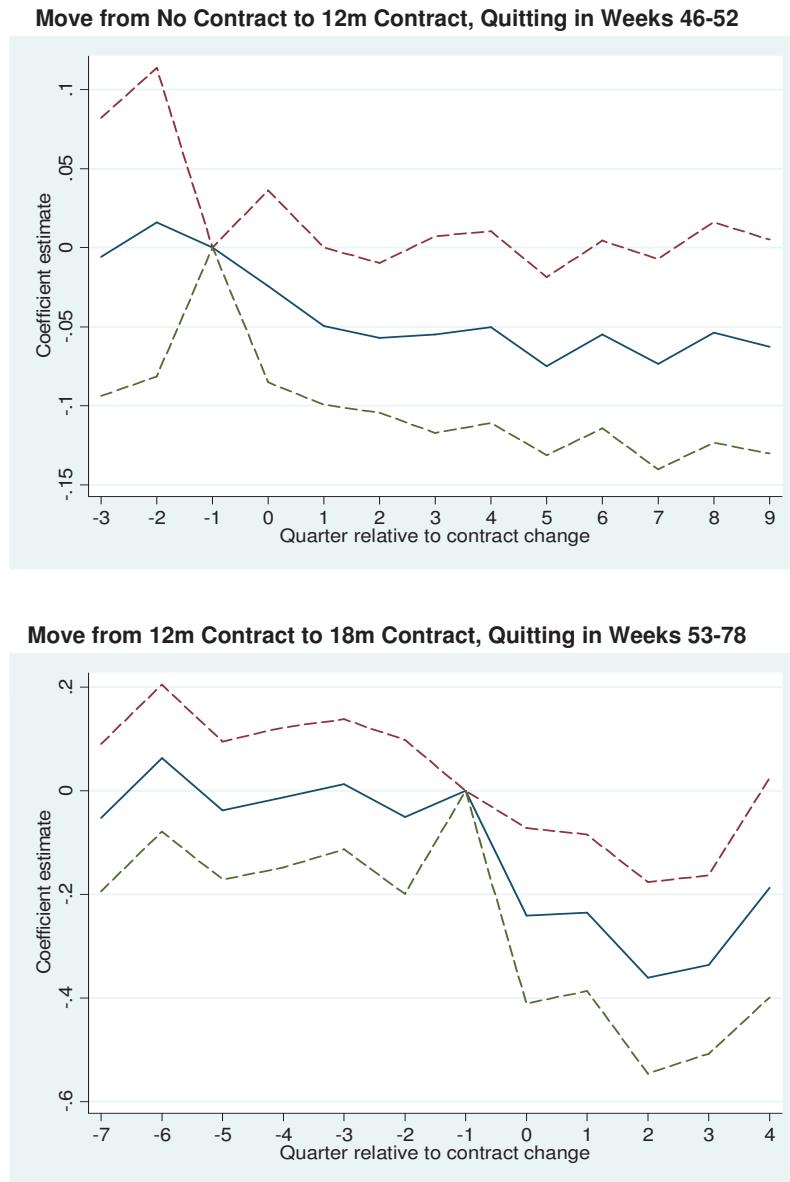
Notes: The sample Size is $0.09N$ with no contract, $0.73N$ with 12m contract, $0.18N$ with 18m contract, $N \gg 5,000$. These figures plot the quitting hazard at any week under the 3 contractual regimes, using all drivers starting at Firm A between 2001 and 2009. The top figure is for the no contract regime, the bottom left is for the 12-month contract regime, and the bottom right is for the 18-month contract regime. An Epanechnikov kernel is used. The bandwidth is 4 weeks for the no contract regime, 2 weeks for the 12-month contract regime, and 3 weeks for the 18 month contract regime. The number of drivers under each of the 3 regimes is listed as the share of all new drivers (N). The exact N is withheld to protect the confidentiality of the firm.

Figure 3: The Impact of Training Contracts on Quitting by Quarter of Tenure (with 95% Confidence Intervals)



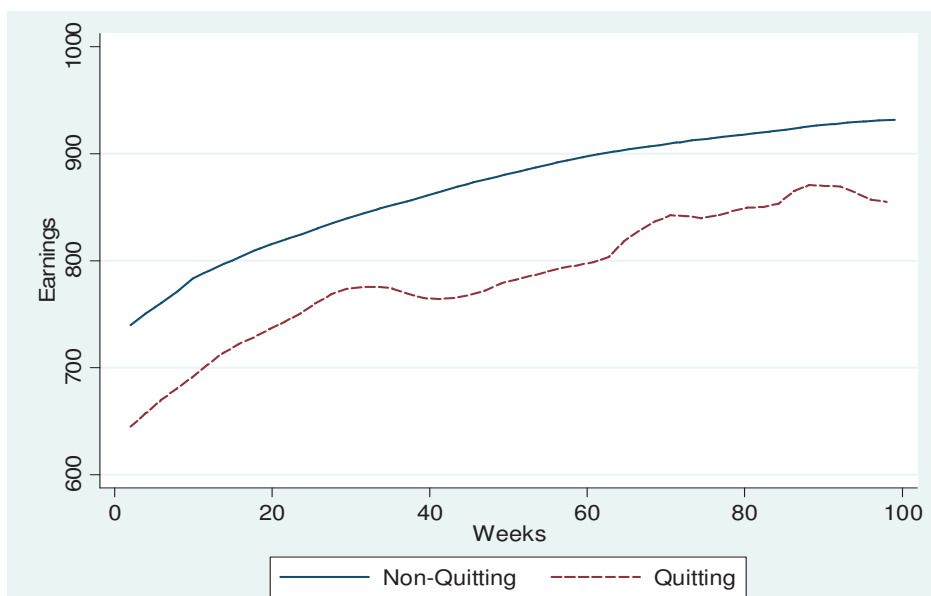
Notes: This figure plots the estimated effect of the two training contracts on quitting at different tenure levels. The solid line denotes the coefficient estimate, with the dotted lines denoting the 95% confidence interval. The coefficients are from OLS regressions of quitting (0 or 1) for a driver in a given week on contract-quarter of tenure interactions and controls, as in Equation (2). Controls include tenure week dummies, year dummies, year of hire dummies, school dummies, annual state unemployment rate, and demographic controls (gender, race, marital status, and driver age). Standard errors are clustered at the school-week of hire level. Under the 12-month contract, quitting is significantly lower (relative to no contract) in the 4th quarter (weeks 39-52), but is somewhat higher (relative to no contract) in the 5th quarter (weeks 53-65). Under the 18-month contract, quitting is significantly lower (relative to no contract) in quarters 4-6, but then increases after that.

Figure 4: Event Studies: The Impact of Training Contracts on Quitting, Comparing Before and After the Contract Changes (with 95% Confidence Intervals)



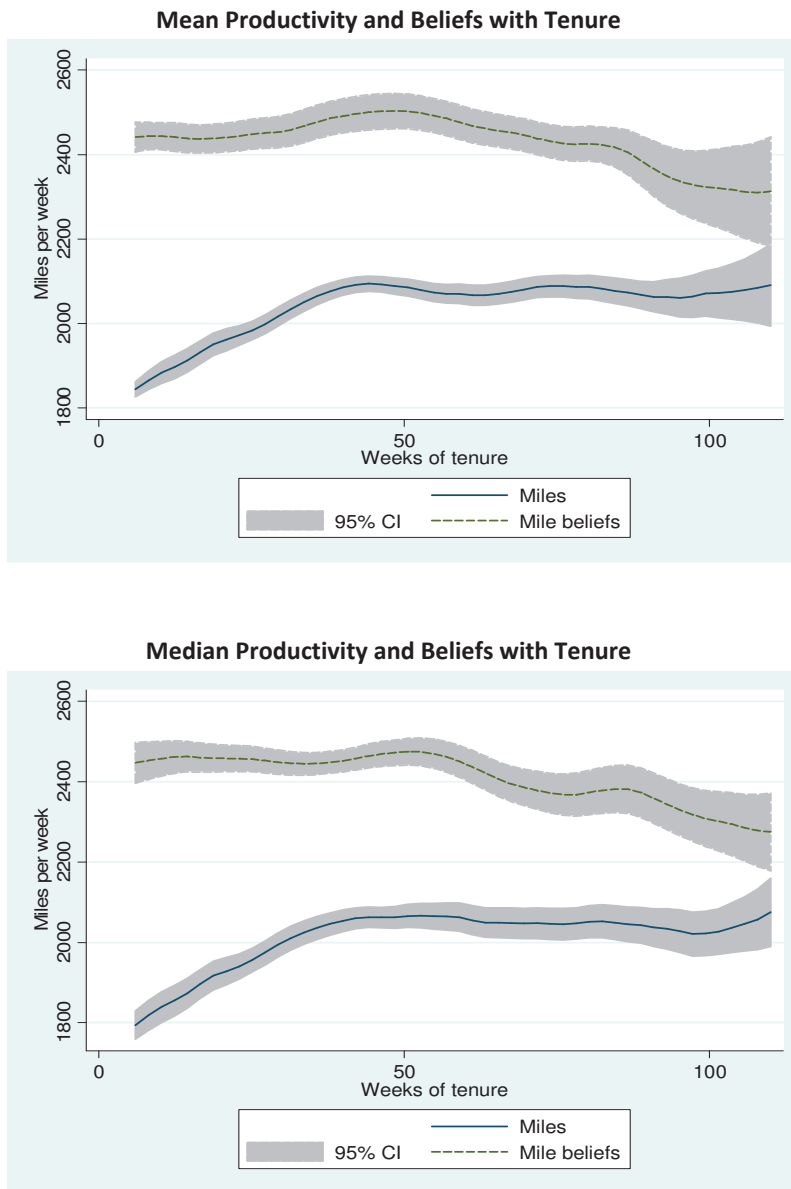
Notes: This figure provides event study estimates of the impacts of the 12-month and 18-month contracts on quitting at the different training schools. The solid line denotes the coefficient estimate, with the dotted lines denoting the 95% confidence interval. The top figure analyzes quitting in weeks 46-52 before and after the change to the 12-month contract whereas the bottom figure analyzes quitting in weeks 53-78 before and after the change to the 18-month contract. The x-axis denotes “event time,” reflecting the contracts being changed at different schools at different times. Each “quarter” refers to the workers hired in a 3-month block. Quarter 0 is the first quarter after the introduction of each training contract. Controls include school fixed effects, year of hire fixed effects, and demographic controls (gender, race, marital status, and driver age), as in Equation (3). Standard errors are clustered at the school-week of hire level.

Figure 5: Quitting and Selection on Productivity: Average Earnings per Week of Quitting and Non-Quitting Drivers



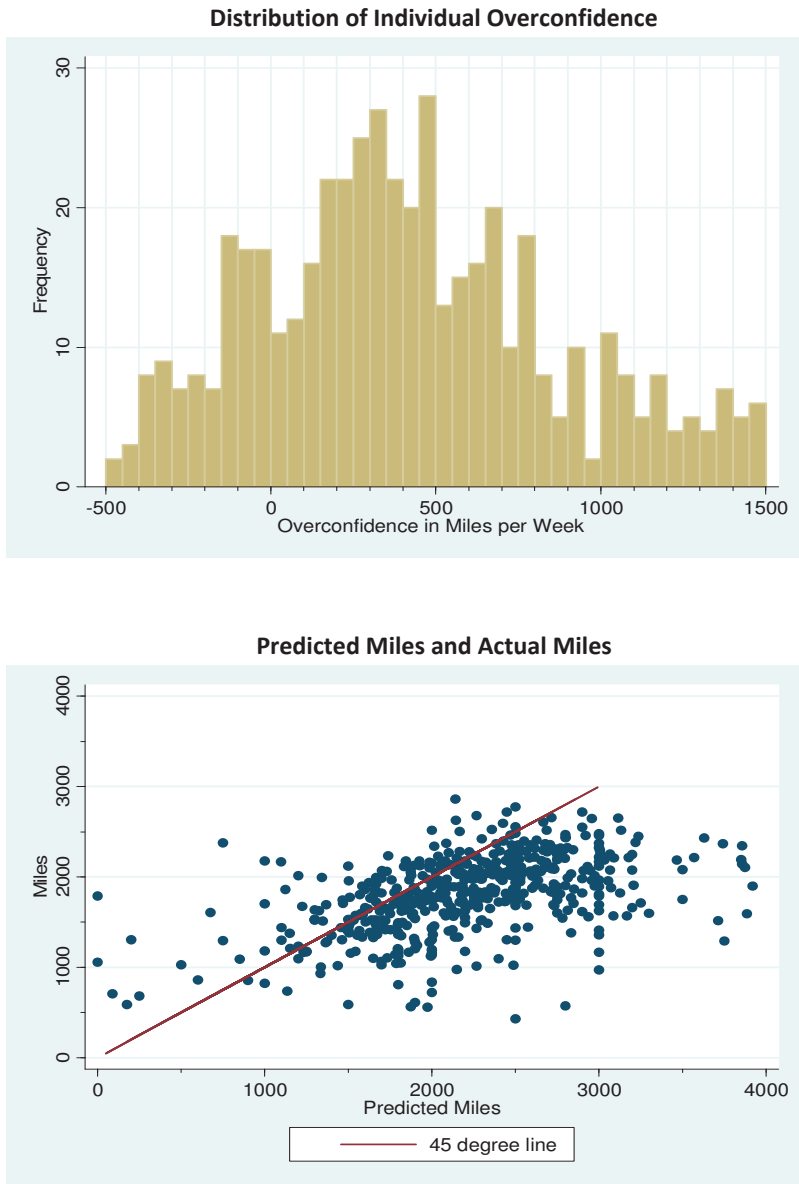
Notes: This figure analyzes the average earnings to date in each week of all new drivers from 2001 to 2009 at Firm A. In each week, it compares the earnings of drivers who quit with those of drivers who do not quit that week. For example, it can be used to compare the average earnings per week (from weeks 1-19) of drivers who quit in the 20th week with the average earnings per week (from weeks 1-19) of drivers who survive to the 20th week, but do not quit. The lines are local polynomials plotted with Stata's `lpoly` command. Zero mile weeks are excluded.

Figure 6: Overconfidence: Comparing Subjective Productivity Forecasts with Actual Worker Productivity (as a Function of Worker Tenure)



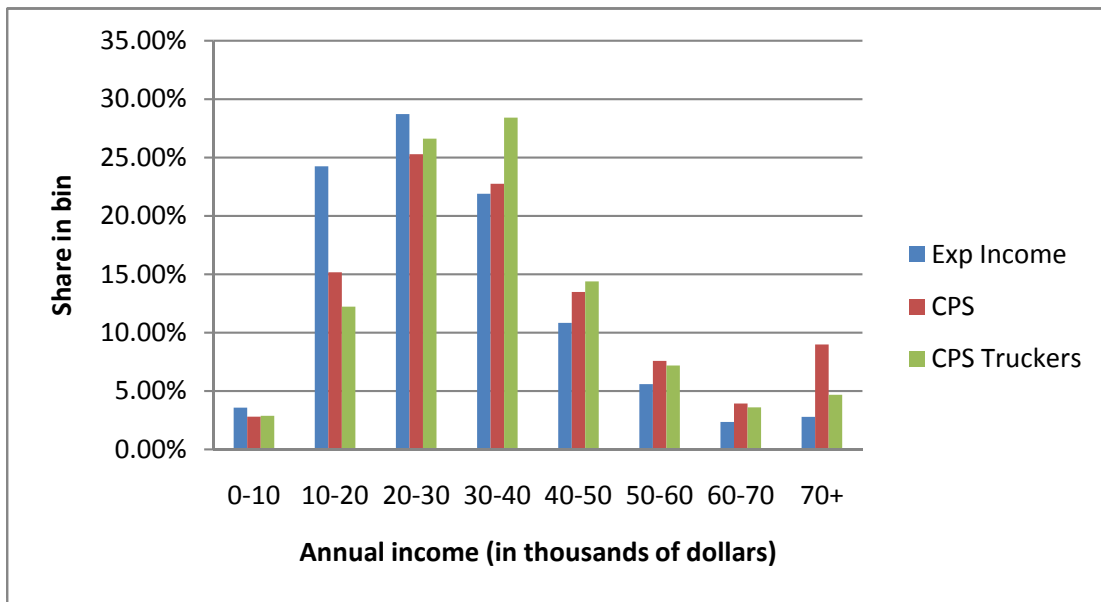
Notes: This figure analyzes actual and believed productivity for 699 drivers in the data subset. The figures are plotted using a local polynomial regression with an Epanechnikov kernel. A bandwidth of 5 weeks is used for the productivity data and a bandwidth of 7 weeks is used for the belief data. In the top figure, the productivity and belief data are collapsed into weekly means before local polynomial smoothing. In the bottom figure, the productivity and belief data are collapsed into weekly medians before local polynomial smoothing.

Figure 7: Distribution of Overconfidence Across Drivers



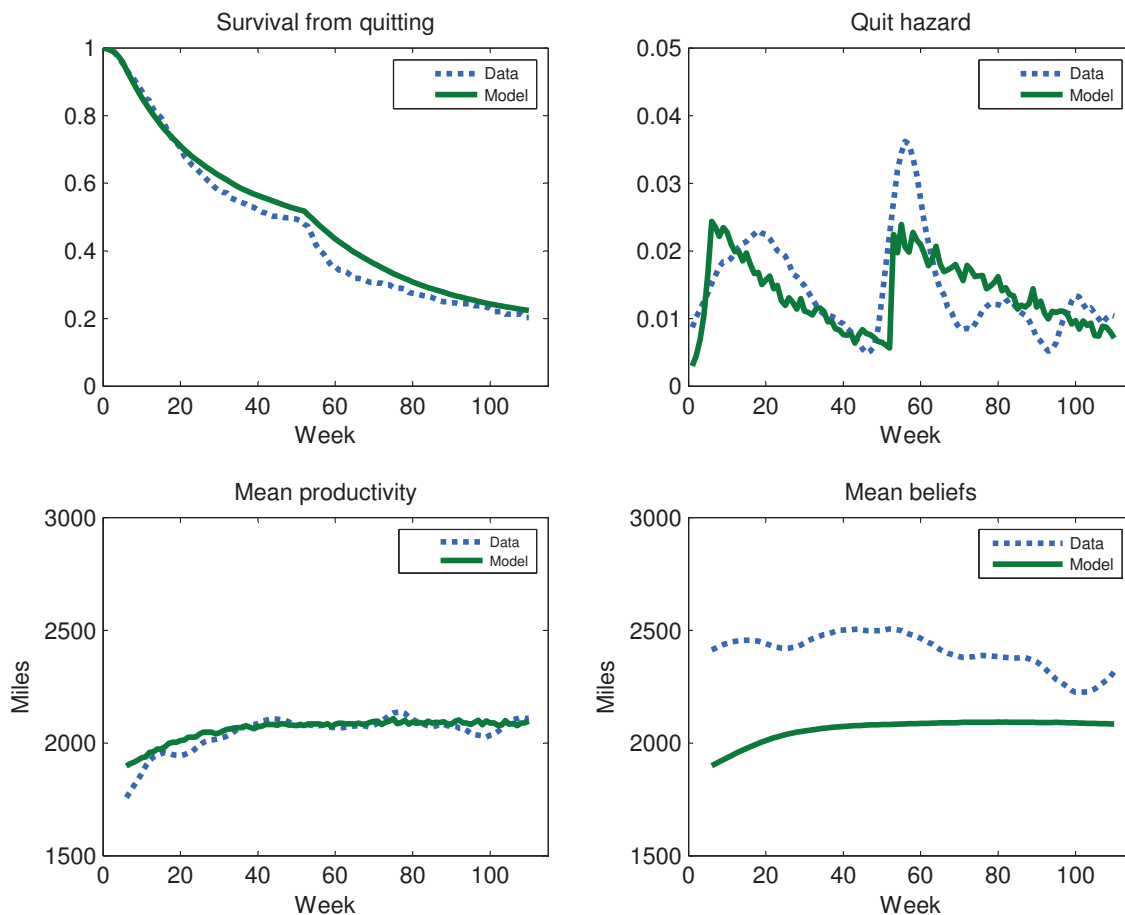
Notes: This figure analyzes overconfidence among 699 drivers in the data subset. It presents reduced-form evidence on the distribution of overconfidence across drivers. The top figure plots a histogram of driver-level overconfidence, where overconfidence is defined as the difference between beliefs and productivity. A driver's overconfidence level is calculated by averaging over all the weeks with productivity beliefs and actual productivity. In the bottom figure, each driver is represented by a dot located at their average productivity and beliefs (averaged over all weeks the driver is observed).

Figure 8: Are Workers Overconfident About their Outside Option? A Comparison of Firm A Workers' Believed Outside Option with Earnings of Similar Workers in the CPS



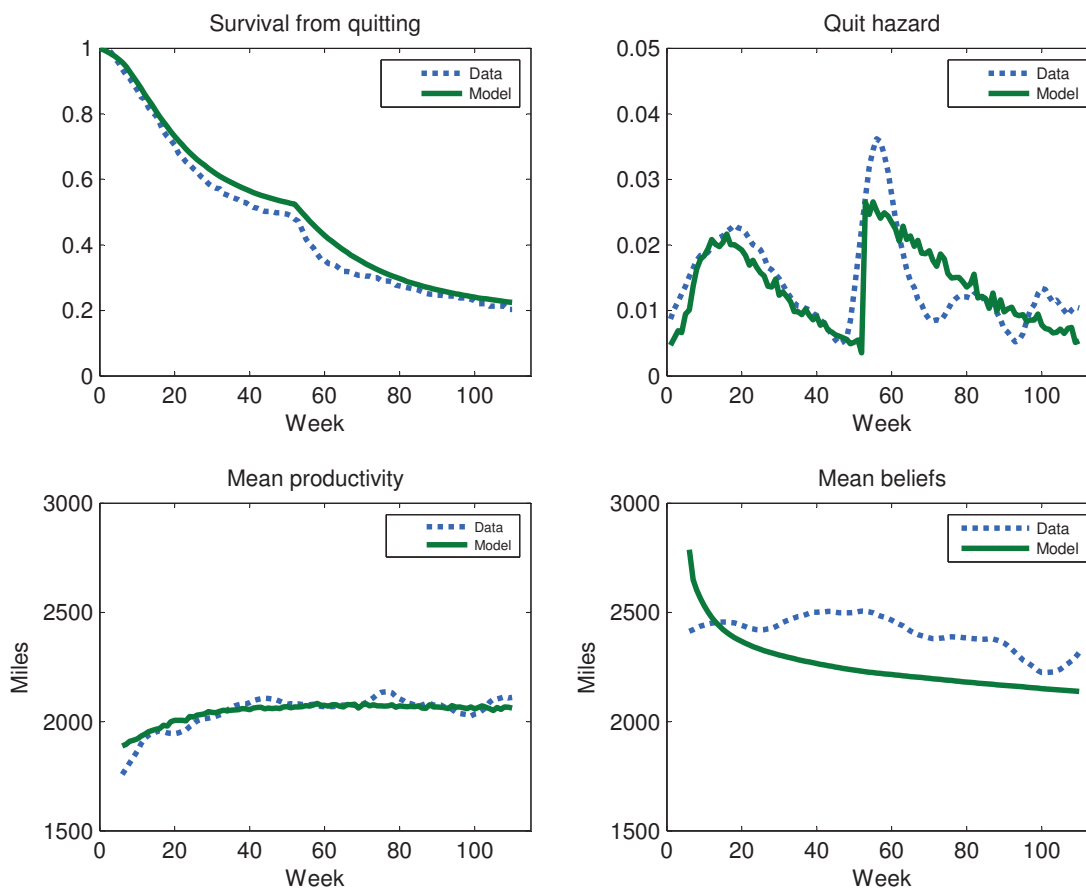
Notes: This figure analyzes worker beliefs about their outside option. During driver training, workers at Firm A were asked “Which range best describes the annual earnings you would normally have expected from your usual jobs (regular and part-time together), if you had not started driver training with [Firm A], and your usual jobs had continued without interruption?” Answers were given in eight intervals: \$0 – \$10,000, \$10,000 – \$20,000, \$20,000 – \$30,000, \$30,000 – \$40,000, \$40,000 – \$50,000, \$50,000 – \$60,000, \$60,000 – \$70,000, \$70,000+. The CPS comparison data is from the 2006 March CPS. “CPS” is the average income and earnings for 35-year old male workers with a high school degree who worked full-time last year. “CPS Truckers” is the average income and earnings for 30-40 year old male workers with a high school degree who work as truckdrivers (Occ=913).

Figure 9: Model Fit, Model Estimated Without Belief Data



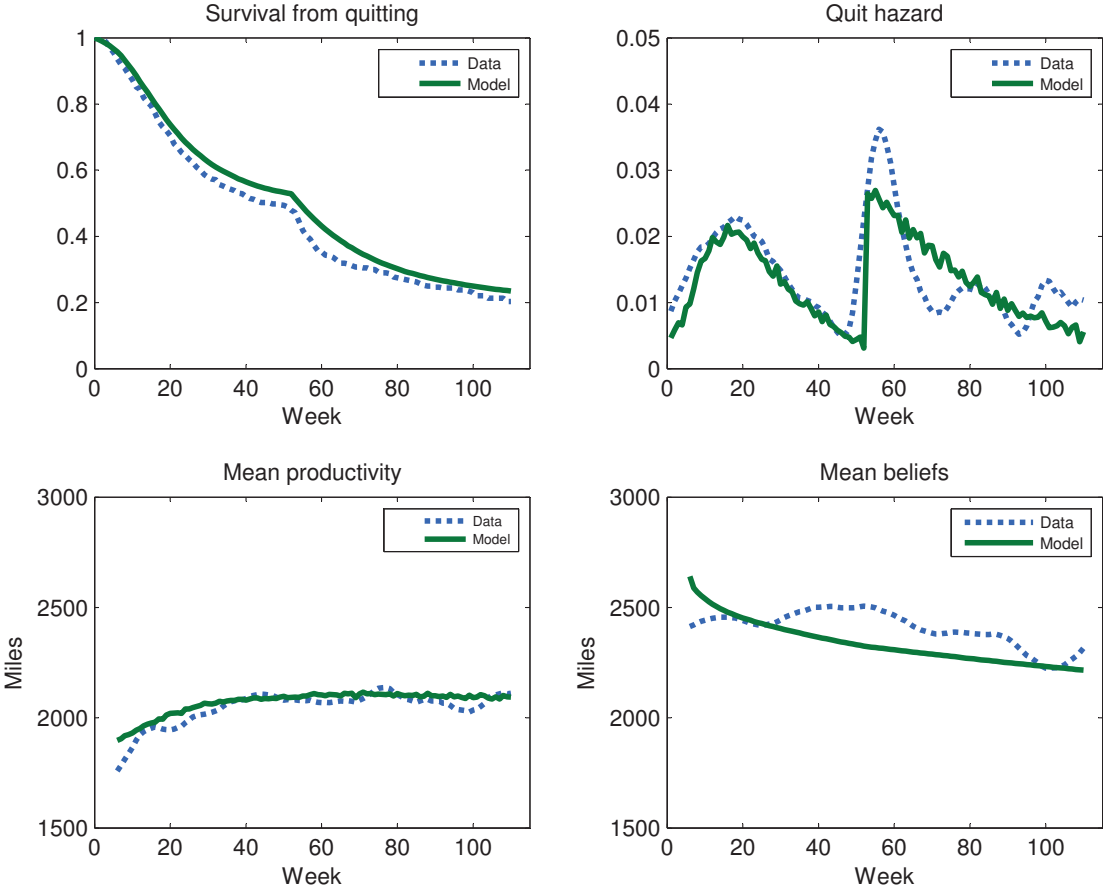
Note: These figures plot the actual hazard rate of quitting against a hazard created from 40,000 simulated drivers. The paths of quits, earnings, and beliefs over tenure are plotted using an Epanechnikov kernel. The bandwidths are 6 weeks, 5 weeks, and 10 weeks for quits, earnings and beliefs, respectively. The data are from 699 drivers under the 12-month contract. A weekly discount factor of 0.9957 is assumed for workers and firms, corresponding to an annual discount factor of 0.8. The model is estimated with learning by doing and allowing for an increasing outside option.

Figure 10: Model Fit, Model Estimated With Overconfidence and Standard Learning



Note: These figures plot the actual hazard rate of quitting against a hazard created from 40,000 simulated drivers. The paths of quits, earnings, and beliefs over tenure are plotted using an Epanechnikov kernel. The bandwidths are 6 weeks, 5 weeks, and 10 weeks for quits, earnings and beliefs, respectively. The data are from 699 drivers under the 12-month contract. A weekly discount factor of 0.9957 is assumed for workers and firms, corresponding to an annual discount factor of 0.8. The model is estimated with learning by doing and allowing for an increasing outside option.

Figure 11: Model Fit for Full Model: Overconfidence and Generalized Learning



Note: These figures plot the actual hazard rate of quitting against a hazard created from 40,000 simulated drivers. The paths of quits, earnings, and beliefs over tenure are plotted using an Epanechnikov kernel. The bandwidths are 6 weeks, 5 weeks, and 10 weeks for quits, earnings and beliefs, respectively. The data are from 699 drivers under the 12-month contract. A weekly discount factor of 0.9957 is assumed for workers and firms, corresponding to an annual discount factor of 0.8. The model is estimated with learning by doing and allowing for an increasing outside option.

Table 1: Summary Statistics

Panel A: All New Drivers at Firm A				
Variable	No Contract	12-Month Contract	18-month Contract	
African-American	0.19	0.19	0.19	
Hispanic	0.07	0.04	0.03	
Female	0.08	0.08	0.08	
Married	0.35	0.35	0.38	
Age	37.27	37.00	37.25	
Online Application	0.47	0.55	0.70	
Smoker	0.30	0.42	0.40	
Drivers	0.09 <i>N</i>	0.73 <i>N</i>	0.18 <i>N</i>	

Panel B: Drivers in Data Subset				
Variable	Obs	Mean	Min	Max
African-American	895	0.11	0	1
Hispanic	895	0.02	0	1
Female	895	0.10	0	1
Married	895	0.41	0	1
Age	894	36.46	21.06	69.21
Number of Kids	895	0.96	0	7
Online Application	889	0.67	0	1
Smoker	787	0.46	0	1
Years of Schooling	895	12.85	9	18
High School Dropout	895	0.04	0	1
High School Graduate	895	0.40	0	1
Some College	895	0.34	0	1
Technical School	895	0.14	0	1
College Degree or More	895	0.08	0	1
Credit Score	784	585.96	407	813
No Credit Score	895	0.12	0	1

Notes: Panel A provides summary statistics for all trained drivers at Firm A from 2001 to 2009. Panel B restricts to drivers in the data subset. Data subset drivers and were hired in late 2005 or 2006. The number of drivers under each of the three contractual regimes is listed as the share of all new drivers (*N*). The exact *N* is withheld to protect the confidentiality of the firm.

Table 2: Impact of the Training Contracts on Quitting – Cox Model, Diff-in-Diff

	(1)	(2)	(3)	(4)	(5)	(6)
12m contract	-0.179*** (0.046)	-0.173*** (0.046)	-0.208*** (0.052)	-0.202*** (0.055)	-0.182*** (0.058)	
18m contract	-0.108* (0.062)	-0.118* (0.062)	-0.116* (0.069)	-0.127* (0.071)	-0.107 (0.074)	
State unemployment rate		-0.055*** (0.011)	-0.048*** (0.013)	-0.062*** (0.013)	-0.049*** (0.014)	-0.054*** (0.014)
Avg miles to date				-0.060*** (0.003)	-0.048*** (0.004)	-0.049*** (0.004)
12m contract * (wks≤52)						-0.371*** (0.074)
12m contract * (52<wks≤78)						0.066 (0.081)
12m contract * (wks>78)						0.043 (0.090)
18m contract * (wks≤52)						-0.021 (0.087)
18m contract * (52<wks≤78)						-0.891*** (0.112)
18m contract * (wks>78)						-0.100 (0.132)
Time FE (yr)	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE (yr of hire)	Yes	Yes	Yes	Yes	Yes	Yes
Training School FE	Yes	Yes	Yes	Yes	Yes	Yes
Demographic Controls	No	No	No	No	Yes	Yes
Observations	<i>M</i>	<i>M</i>	0.89 <i>M</i>	0.89 <i>M</i>	0.79 <i>M</i>	0.79 <i>M</i>

Notes: An observation is a driver-week. The regressions are Cox proportional hazard models, with standard errors clustered by school-week of hire in parentheses. Driver tenure is controlled for non-parametrically. State unemployment is a state's annual unemployment rate. Demographic controls include gender, race dummies, marital status, and driver age. Average miles to date is a driver's average weekly productivity to date and is given in terms of hundreds of miles driven per week. Column (3) differs from column (2) in that it restricts the sample to be the same as in column (4). The exact *M* is withheld to protect firm confidentiality, $M \gg 100,000$. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 3: Selection Effects of Training Contracts

Panel A: Selection on Productivity						
	All Weeks		Exclude 0 Mile Weeks		Trim 5/95%	
	(1)	(2)	(3)	(4)	(5)	(6)
12m contract	0.17 (28.59)	-7.01 (28.55)	24.69 (23.95)	21.1 (23.63)	23.74 (18.68)	22.01 (18.58)
18m contract	-21.56 (31.01)	-25.44 (31.29)	11.78 (28.72)	8.31 (28.60)	13.62 (22.06)	10.37 (22.12)
Demog controls	No	Yes	No	Yes	No	Yes
Mean Dep. Var:	1661	1690	1963	1956	1951	1947
Observations	0.99M	0.86M	0.84M	0.74M	0.75M	0.67M
R-squared	0.24	0.22	0.05	0.05	0.04	0.04

Panel B: Selection on Other Characteristics							
Dep. Var:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Black	Hispanic	Female	Married	Age	Smoker	Online Ap
12m contract	-0.009 (0.014)	0.021** (0.010)	0.012 (0.010)	-0.016 (0.017)	0.111 (0.399)	0.050* (0.027)	0.055** (0.022)
18m contract	0.006 (0.020)	0.014 (0.013)	0.023 (0.015)	-0.005 (0.024)	0.574 (0.541)	0.062* (0.033)	0.047* (0.028)
Observations	N	N	N	N	0.72N	0.70N	0.82N
R-squared	0.03	0.03	0.01	0.01	0.01	0.02	0.07

Notes: Panel A reports OLS regressions of productivity (miles per week) on training contract dummies and controls. In Panel A, an observation is a driver-week. “Trim 5/95%” refers to trimming the lowest 5% and highest 5% of the miles observations (ignoring all 0 mile weeks). Panel B reports OLS regressions of driver characteristics on training contract dummies and controls. In Panel B, an observation is a driver. Standard errors clustered by school-week of hire in parentheses. The exact M (driver weeks) and N (drivers) are withheld to protect firm confidentiality, $M \gg 100,000$. All regressions include time fixed effects (for each month), cohort fixed effects (by year of hire), tenure fixed effects (by week), work type controls, and the annual state unemployment rate. Demographic controls include gender, race dummies, marital status, and driver age. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 4: Do Productivity Beliefs Predict Productivity? OLS Regressions

	(1)	(2)	(3)	(4)	(5)
L. Pred miles	0.195*** (0.023)	0.066*** (0.016)	0.064*** (0.016)	0.079*** (0.022)	0.086*** (0.023)
L. Avg miles to date		0.789*** (0.037)	0.689*** (0.038)		-0.188* (0.108)
Tenure FE	No	Yes	Yes	Yes	Yes
Demographic Controls	No	No	Yes	No	No
Education Controls	No	No	Yes	No	No
Work Type Controls	No	No	Yes	No	No
Subject FE	No	No	No	Yes	Yes
Observations	8,449	8,435	8,435	8,449	8,435
R-squared	0.05	0.17	0.18	0.29	0.29

Notes: The dependent variable is miles driven per week. An observation is a driver-week. Standard errors clustered by driver in parentheses. Demographic controls include gender, race dummies, marital status, and age bin dummies for the different age groups: 25-30, 30-35, 35-40, 40-45, 45-50, 50-55, 55-60, and 60-80. Education controls are dummies for high school graduate, some college, and college. Work type controls are dummies for different work configurations and for receiving any salary or activity-based pay. Productivity is given in terms of hundreds of miles driven per week. All drivers are from the same training school and were hired in late 2005 or 2006. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 5: Do Productivity Beliefs Predict Quitting?

	(1)	(2)	(3)	(4)	(5)
Predicted miles	-0.059*** (0.018)			-0.059*** (0.020)	-0.067*** (0.021)
Avg miles to date		-0.079*** (0.010)	-0.112*** (0.039)	-0.002 (0.036)	-0.062 (0.042)
Demographic Controls	No	Yes	Yes	No	Yes
Education Controls	No	Yes	Yes	No	Yes
Work Type Controls	No	Yes	Yes	No	Yes
Observations	8,500	38,381	8,500	8,500	8,500

Notes: An observation is a driver-week. The regressions are Cox proportional hazard models, where the dependent variable is quitting. Events where the driver is fired are treated as censored. Standard errors clustered by worker are in parentheses. Demographic controls include gender, race dummies, marital status, and age bin dummies for the different age groups: 25-30, 30-35, 35-40, 40-45, 45-50, 50-55, 55-60, and 60-80. Education controls are dummies for high school graduate, some college, and college. Work type controls are dummies for different work configurations and for receiving any salary or activity-based pay. Productivity is given in terms of hundreds of miles driven per week. All drivers are from the same training school and were hired in late 2005 or 2006. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 6: Baseline Structural Estimates

		No Bias	Belief Bias	Belief Bias 2 Types
τ	Scale param of idiosyncratic shock	1618 (136)	2206 (291)	3726 (449)
	<u>Productivity Parameters</u>			
η_0	Mean of prior productivity dist	2464 (9)	2025 (17)	2024 (18)
σ_0	Std dev of prior productivity dist	475 (16.5)	286 (10.1)	284 (9.9)
σ_y	Std dev of productivity shocks	707 (1.5)	706 (1.5)	706 (1.6)
	<u>Skill Gain Parameter</u>			
s_0	Value of skills gained in wks 1-5	14.9 (3.5)	8.6 (5.9)	31.7 (9.0)
	<u>Taste UH Parameters</u>			
μ_1	Mass point 1 of taste UH	-248 (9.0)	-259 (12.6)	-736 (41.9)
μ_2	Mass point 2 of taste UH	-106 (14.6)	-135 (12.1)	-150 (10.0)
μ_3	Mass point 3 of taste UH	139 (39.3)	135 (33.3)	191 (63.1)
p_1	Probability of type 1, taste	0.55 (0.04)	0.34 (0.06)	0.12 (0.03)
p_2	Probability of type 2, taste	0.24 (0.03)	0.43 (0.06)	0.67 (0.04)
	<u>Belief Parameters</u>			
σ_b	Std dev in beliefs	299 (0.3)	298 (0.3)	271 (0.3)
$\widetilde{\sigma}_y$	Believed std dev of productivity shocks	3650 (134)	1888 (82)	2068 (81)
η_b	Belief bias		589 (22)	
$\eta_{1,b}$	Mass point 1 of belief UH			426 (20)
$\eta_{2,b}$	Mass point 2 of belief UH			3649 (41)
$p_{1,b}$	Probability of type 1, beliefs			0.94 (0.16)
	Log-likelihood	-91064	-90865	-89882
	Number of workers	699	699	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. Standard errors are in parentheses and are calculated by inverting the Hessian. All specifications assume a normal learning model. 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.

Table 7: Structural Estimates with Learning by Doing and Skill Accumulation

		No Bias	Belief Bias	Belief Bias 2 Types
τ	Scale param of idiosyncratic shock	1891 (260)	1605 (180)	4207 (925)
	<u>Productivity and Skill Parameters</u>			
η_0	Mean of prior productivity dist	2307 (28)	1595 (41)	1742 (33)
σ_0	Std dev of prior productivity dist	521 (20.8)	275 (10.5)	276 (10.5)
σ_y	Std dev of productivity shocks	706 (3.6)	706 (3.6)	705 (3.6)
b_1	Learning by doing level	251 (33)	485 (38)	343 (34)
b_2	Learning by doing speed	0.08 (0.01)	0.11 (0.02)	0.07 (0.01)
θ_1	Skill gain level	92 (53)	228 (54)	534 (140)
θ_2	Skill gain speed	0.68 (0.30)	0.03 (0.01)	0.05 (0.01)
	<u>Taste UH Parameters</u>			
μ_1	Mass point 1 of taste UH	-195 (56.7)	-345 (19.7)	-988 (211.6)
μ_2	Mass point 2 of taste UH	-61 (58.1)	-81 (30.0)	27 (58.5)
μ_3	Mass point 3 of taste UH	180 (73)	231 (55)	634 (170)
p_1	Probability type 1	0.55 (0.07)	0.60 (0.04)	0.42 (0.06)
p_2	Probability of type 2	0.25 (0.06)	0.19 (0.04)	0.35 (0.06)
	<u>Belief Parameters</u>			
σ_b	Std dev in beliefs	298 (1.4)	297 (1.4)	271 (1.3)
$\widetilde{\sigma}_y$	Believed std dev of productivity shocks	3481 (167)	1295 (82)	1759 (108)
η_b	Belief bias		722 (31)	
$\eta_{1,b}$	Mass Point 1 of belief UH			466 (25)
$\eta_{2,b}$	Mass Point 2 of belief UH			3899 (139)
p_1	Prob of Type 1			0.93 (0.01)
	Log-likelihood	-91024	-90731	-89787
	Number of workers	699	699	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. Standard errors are in parentheses and are calculated by inverting the Hessian. All specifications assume a normal learning model. 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.

Table 8: Profits and Welfare Under Different Contracts

	No contract	12 month	18 month
Profits per worker	\$363	\$1,625	\$1,875
Profits per truck	-\$2,544	\$1,856	\$2,641
Welfare per worker	\$159,580	\$156,590	\$156,375

Notes: This table presents profits per worker and profits per worker under the three different training contracts used by Firm A. Profits per worker and profits per firm are defined in Section 9 of the text. Profits are calculated assuming a Fixed Cost of \$600 per week, a price of \$1.80 per mile, a non-wage marginal cost of \$1.16 per mile, a sunk cost of \$2.50 per worker per week, and a marginal cost of training of \$2,500, and a collection rate of 30%. Profits and welfare are calculated by simulating 40,000 workers under each of the three regimes. A weekly discount factor of 0.9957 is assumed for workers and firms, corresponding to an annual discount factor of 0.8. The model is estimated with 3 taste mass points and 2 overconfidence mass points. The model simulated has no learning by doing and assumes a flat outside option after the first 5 weeks.

Table 9: Counterfactual Simulations, No Contractual Response

	Baseline	50% debias	100% debias	Reveal ability
Retention at 20 wks	0.74	0.62	0.49	0.45
Retention at 40 wks	0.55	0.44	0.32	0.32
Retention at 60 wks	0.43	0.35	0.26	0.26
Welfare per worker	\$156,590	\$157,771	\$158,708	\$158,959
Profits per worker	\$1,625	\$793	-\$83	\$562
Profits per truck	\$1,856	-\$1,159	-\$5,225	-\$2,650
Ability at 20 wks	2,037	2,034	2,036	2,085
Ability at 40 wks	2,058	2,055	2,053	2,115
Ability at 60 wks	2,072	2,062	2,057	2,114

Notes: This table reports the reports the results of the counterfactual simulations described in the text, while assuming that training contracts are not adjusted in response. Under the 50% debias and 100% debias counterfactuals, worker overconfidence is reduced by 50% or 100% (by reducing the overconfidence mass points η_{b1} and η_{b2} by 50% or 100%). Under the reveal ability counterfactual, the worker's ability is revealed to the worker after training. Profits are calculated assuming a Fixed Cost of \$600 per week, a price of \$1.80 per mile, a non-wage marginal cost of \$1.16 per mile, a sunk cost of \$2.50 per worker per week, and a marginal cost of training of \$2,500, and a collection rate of 30%. A weekly discount factor of 0.9957 is assumed for workers and firms, corresponding to an annual discount factor of 0.8. The model is estimated with 3 taste mass points and 2 overconfidence mass points. The model simulated has no learning by doing and assumes a flat outside option after the first 5 weeks.

Table 10: Counterfactual Simulations Allowing for Optimal Contractual Responses

	Baseline	50% debias	100% debias	Reveal ability	Ban training contracts	Ban training contracts + 50% debias
Optimal 12m penalty	\$11,400	\$8,600	\$0	\$0	NA	NA
Wage factor	1.022	1.026	0.918	0.909	0.983	0.965
Retention at 20 wks	0.86	0.76	0.38	0.36	0.64	0.51
Retention at 40 wks	0.80	0.65	0.23	0.22	0.41	0.33
Retention at 60 wks	0.66	0.52	0.20	0.18	0.31	0.26
Welfare per worker	\$153,622	\$155,653	\$159,177	\$159,265	\$159,247	\$159,852
Profits per worker	\$2,070	\$1,311	\$705	\$1,278	\$708	\$334
Profits per truck	\$3,129	\$969	-\$2,904	-\$317	-\$1,508	-\$3,566
Ability at 20 wks	2,025	2,032	2,033	2,084	2,035	2,031
Ability at 40 wks	2,032	2,049	2,041	2,115	2,056	2,047
Ability at 60 wks	2,052	2,066	2,043	2,109	2,057	2,049

Notes: This table reports the results of the counterfactual simulations described in the text, while assuming that training contracts are optimally adjusted in response. Under the 50% debias and 100% debias counterfactuals, worker overconfidence is reduced by 50% or 100% (by reducing the overconfidence mass points η_{b1} and η_{b2} by 50% or 100%). Under the reveal ability counterfactual, the worker's ability is revealed to the worker after training. Under the ban training contracts counterfactual, firms are forbidden from charging a quitting penalty. Profits are calculated assuming a Fixed Cost of \$600 per week, a price of \$1.80 per mile, a non-wage marginal cost of \$1.16 per mile, a sunk cost of \$2.50 per worker per week, and a marginal cost of training of \$2,500, and a collection rate of 30%. A weekly discount factor of 0.9957 is assumed for workers and firms, corresponding to an annual discount factor of 0.8. The model is estimated with 3 taste mass points and 2 overconfidence mass points. The model simulated has no learning by doing and assumes a flat outside option after the first 5 weeks.

A Model for Section 3.1

In this section, I present a model of training contracts and turnover to accompany the discussion in Section 3.1. I show how training contracts can increase training and reduce turnover. In addition, I show how worker overconfidence about ability can also increase training, and how overconfidence and training contracts can be complimentary. The model has one period and abstracts from the dynamics considered in the structural model. The model is fairly similar to that in Peterson (2010), with one difference being that I assume monopsony in the market for training whereas Peterson (2010) assumes perfect competition. Both of us allow for competition in the post-training labor market.

Consider a firm which trains its workers. Workers have an initial productivity of zero at the firm and an outside option of r . A training investment is available at cost c that raises productivity from 0 to η . Workers have some non-pecuniary taste for the job ε , which they learn after training. I assume that ε has a distribution function F and has support over the entire real line. Let $\Psi(x) = 1 - F(x)$, that is, $\Psi(\cdot)$ is the survival function. I assume that the function $x \mapsto x\Psi^{-1}(x)$ is concave. If the firm chooses to train, it also chooses a piece rate w to pay. That is, the worker's total wage will be given by $W = w\eta$. 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 \bar{W} minus any training contract k . I assume only that the outside option after training is greater than or equal to the worker's outside option before training ($\bar{W} \geq r$). The case of $\bar{W} = r$ corresponds to the worker choosing whether to go to another occupation whereas $\bar{W} = \eta$ may correspond to the worker choosing to leave for another firm within the same occupation (if training is portable across firms, but occupation-specific). I assume that the training contract is experienced fully by the worker, but that only a share $\theta \in [0, 1]$ of the contract is collected.

The timing of the model is as follows:

1. The firm chooses whether to train, and if so, sets w and the level of the training contract.
2. The worker decides whether or not to accept the contract.
3. The taste shock ε is realized, the worker decides whether to quit, and payoffs are realized.

The firm's problem can be written as:

$$\begin{aligned} & \max_{w,k} (1 - F(-w\eta - k + \bar{W})) * (\eta - w\eta) + F(-w\eta - k + \bar{W})\theta k - c \\ r & \leq E \max(w\eta + \varepsilon, \bar{W} - k) \end{aligned}$$

I first prove the following proposition.

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

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

$$\begin{aligned} f(-W - k + \bar{W})(\eta - W - \theta k) - (1 - F(-W - k + \bar{W})) + \lambda \frac{\partial Emax}{\partial W} &= 0 \\ f(-W - k + \bar{W})(\eta - W - \theta k) + \theta F(-W - k + \bar{W}) + \lambda \frac{\partial Emax}{\partial k} &= 0 \end{aligned}$$

If $\lambda = 0$, an interior solution exists only if $(1 - F(-W - k + \bar{W})) = -\theta F(-W - k + \bar{W})$, which is not possible for $\theta > 0$.⁷⁹ Because it is not possible to satisfy the IR constraint while setting $k = 0$ (since $\bar{W} \geq r$ and ε has full support over the real line), $k = 0$ cannot be optimal.⁸⁰

To analyze retention, let P denote the retention probability.⁸¹ Note then that $W = (\bar{W} - k - \Psi^{-1}(P))$. Profits are then given by:

$$\begin{aligned} P \times (\eta - W) + (1 - P)\theta k - c &= P \times (\eta - (\bar{W} - k - \Psi^{-1}(P))) + (1 - P)\theta k - c \\ &= P(\eta - \bar{W}) + k(P + (1 - P)\theta) + P\Psi^{-1}(P). \end{aligned} \tag{14}$$

⁷⁹The boundary solutions for the unconstrained problem are to have W to go minus infinity and k go to positive infinity faster (all worker stay and get paid minus infinity) or to have W go to minus infinity and have k go to minus infinity slower (all workers quit and firm collects infinity from them). Both of these solutions violate the IR constraint.

⁸⁰Setting W to infinity is clearly suboptimal. When W is negative and large in magnitude, the derivative wrt W may be positive. When k is a large number, the derivative may be negative. Setting k to minus infinity is clearly suboptimal.

⁸¹I am grateful to Ben Hermalin for greatly simplifying the proof that retention increases.

Note that the IR constraint can be written as $r \leq \mathbb{E}max\{\bar{W} - \Psi^{-1}(P) - k + \varepsilon, \bar{W} - k\}$ or as $r \leq \mathbb{E}max\{\varepsilon - \Psi^{-1}(P), 0\} + \bar{W} - k$. 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

$$\eta - \bar{W} + \Psi^{-1}(P) + P\Psi^{-1'}(P) = 0. \quad (15)$$

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

$$\eta - \bar{W} + \Psi^{-1}(P) + P\Psi^{-1'}(P) + k'(P) \times (P + (1 - P)\theta) + k(1 - \theta) = 0. \quad (16)$$

Given that $k'(P) \times (P + (1 - P)\theta) + k(1 - \theta)$ is positive for all P and that $\Psi^{-1}(P) + P\Psi^{-1'}(P)$ is decreasing in P (by the concavity of $P\Psi^{-1}(P)$), it follows that the P that solves Equation (16) (where the firm optimally sets k) is greater than the P that solves Equation (15) (where $k = 0$).⁸² ■

Next, I examine the impact of productivity overconfidence of workers becoming more overconfident on the probability of training. The idea is that as workers become more overconfident about their productivity, it is easier to get them to agree to work for a given wage at a given training contract and they become less likely to quit afterward for a given wage. I first consider overconfidence that persists after the worker goes through training. After this, I will consider overconfidence that goes away after training via learning. When workers have biased beliefs, the firm's problem can be written as

$$\begin{aligned} \arg \max_{w, k} (1 - F(-w\eta' - k + \bar{W})) * (1 - w)\eta + F(-w\eta' - k + \bar{W})\theta k - c \\ Emax(w\eta' + \varepsilon, \bar{W} - k) \geq r \end{aligned}$$

where η' is the worker's belief about his productivity.

Proposition 2 *An increase in permanent overconfidence leads to a higher likelihood of training, both when training contracts are available and when they are unavailable, provided that the worker perceives his current earnings to be more responsive to his current productivity than his outside option. Formally, suppose that $w > \frac{d\bar{W}}{d\eta'}$, where w solves $\eta - w\eta = G(-w\eta + \bar{W})$; then an increase in η' increase the probability of training.*

Proof. Note that the outside option \bar{W} may depend on η' . Start with when k is restricted to be zero. Let w^* denote the optimal salary if workers had rational beliefs. If workers believe their productivity will be $\eta' > \eta$, setting a wage of w^* is still feasible (as $Emax(w\eta' + \varepsilon, \bar{W}) > Emax(w\eta + \varepsilon, \bar{W})$). Further, given the rational wage w^* , an increase in productivity beliefs increases profits so long as $sgn\left(\frac{\partial(1 - F(-w\eta' - k + \bar{W}))}{\partial\eta'}\right) = sgn\left(-f * \left(-w + \frac{d\bar{W}}{d\eta'}\right)\right) = sgn\left(w - \frac{d\bar{W}}{d\eta'}\right) = +$. Since using the rational belief wage results in higher profits when workers have biased beliefs than when they are rational, optimal wage profits must increase when workers have biased beliefs. When the firm sets optimal w and k , the argument is similar. Let (w^*, k^*) denote the optimal wage and training contract when workers are rational. Setting (w^*, k^*) is still feasible if workers come to believe their productivity will be $\eta' > \eta$ and increasing beliefs from η to η' increases profits under (w^*, k^*) so long as $w > \frac{d\bar{W}}{d\eta'}$ and $(1 - w)\eta - \theta k > 0$. ■

From this claim, we learned that overconfidence can make training profitable for firms when they are using training contracts. In the next claim, I consider the case where workers are overconfident, but this overconfidence disappears after training. In this case, overconfidence increases training when training contracts are available, but not if training contracts are unavailable.

Proposition 3 *An increase in non-permanent overconfidence leads to a higher likelihood of training when training contracts are available, but has no effect when training contracts are not available.*

Proof. Recall that the IR constraint is slack when a training contract is not available. Since non-permanent overconfidence will only affect the IR constraint, the overconfidence has no effect on profitability. However, when a training contract is available, the IR constraint must bind. An increase in overconfidence can be combined with either a decrease in wage or an increase in k , and the IR constraint will still hold, thereby increasing profits. ■

⁸²Indeed, one can show that retention is highest in the problem where the firm optimally sets k compared to any other situation where k is exogenous.

B Structural Model Derivations

One of the key equation in the model is the expected maximum or Emax term. I have that:⁸³

$$\begin{aligned}
E(V_{t+1}(\mathbf{x}_{t+1})|\mathbf{x}_t) &= E_{y_t} E_{\epsilon|y_t}(V_{t+1}(\mathbf{x}_{t+1})|\mathbf{x}_t) \\
&= E_{y_t} E_{\epsilon}(V_{t+1}(\mathbf{x}_{t+1})|\mathbf{x}_t) \\
&= E_{y_t} E_{\epsilon}(\max\{\bar{V}_{t+1}^S(\mathbf{x}_{t+1}) + \epsilon_{t+1}^S, \bar{V}_{t+1}^Q + \epsilon_{t+1}^Q\}|\mathbf{x}_t) \\
&= \int E_{\epsilon}(\max\{\bar{V}_{t+1}^S(\mathbf{x}_{t+1}) + \epsilon_{t+1}^S, \bar{V}_{t+1}^Q + \epsilon_{t+1}^Q\}|\mathbf{x}_{t+1}) f^b(y_t|y_1, \dots, y_{t-1}) dy_t \\
&= \int \tau \log \left(\exp\left(\frac{\bar{V}_{t+1}^S(\mathbf{x}_{t+1})}{\tau}\right) + \exp\left(\frac{\bar{V}_{t+1}^Q}{\tau}\right) \right) f^b(y_t|y_1, \dots, y_{t-1}) dy_t \\
&= \sum_k \tau \log \left(\exp\left(\frac{\bar{V}_{t+1}^S(\mathbf{x}_{t+1})}{\tau}\right) + \exp\left(\frac{\bar{V}_{t+1}^Q}{\tau}\right) \right) \Pr(y_t^k|y_1, \dots, y_{t-1}).
\end{aligned}$$

The first equality expresses that the value function depends on future earnings and future idiosyncratic shocks. The second equality follows because future earnings are independent of the idiosyncratic shocks. The third equality uses the definition of V and that V_s^Q is independent of the state variable. The fourth equality integrates out y_t , which are not observed when the driver makes his period t decision, but are observed in the future. The fifth equality integrates out the idiosyncratic shocks. The last equality follows because, in implementation, earnings will be discretized into K possible values. The probability $\Pr(y_t^k|y_1, \dots, y_{t-1})$ can be easily shown to depend only on \bar{y}_{t-1} , and is expressed below. As long as average earnings to date by time $t+1$, \bar{y}_t , is a sufficient statistic for x_{t+1} , then it follows that average earnings by time t , \bar{y}_{t-1} , is a sufficient statistic for x_t .

Collecting terms from the model, I show how to derive the likelihood function:

$$\begin{aligned}
L_i &= \int L(d_{i1}, \dots, d_{it}, y_{i1}, \dots, y_{it}, b_{i1}, \dots, b_{it} | \alpha, \eta_b) f(\alpha, \eta_b) d\alpha d\eta_b \\
&= \int \{L(d_{i1}, \dots, d_{it} | y_{i1}, \dots, y_{it}, b_{i1}, \dots, b_{it}, \alpha, \eta_b) * L(b_{i1}, \dots, b_{it} | y_{i1}, \dots, y_{it}, \alpha, \eta_b) \\
&\quad * L(y_{i1}, \dots, y_{it} | \alpha, \eta_b) f(\alpha, \eta_b) d\alpha d\eta_b\} \\
&= \int \{L(d_{i1}, \dots, d_{it} | y_{i1}, \dots, y_{it}, b_{i1}, \dots, b_{it}, \alpha, \eta_b) * L(b_{i1}, \dots, b_{it} | y_{i1}, \dots, y_{it}, \eta_b) \\
&\quad * L(y_{i1}, \dots, y_{it}) f(\alpha, \eta_b) d\alpha d\eta_b\} \\
&= \left\{ \int L(d_{i1}, \dots, d_{it} | y_{i1}, \dots, y_{it}, \alpha, \eta_b) * L(b_{i1}, \dots, b_{it} | y_{i1}, \dots, y_{it}, \eta_b) f(\alpha, \eta_b) d\alpha d\eta_b \right\} L(y_{i1}, \dots, y_{it}) \\
&= \left[\int \prod_{s=1}^t L(d_{is} | d_{i1}, \dots, d_{is-1}, y_{i1}, \dots, y_{it}, \alpha, \eta_b) * \prod_{s=1}^t L(b_{is} | b_{i1}, \dots, b_{is-1}, y_{i1}, \dots, y_{it}, \eta_b) f(\alpha, \eta_b) d\alpha d\eta_b \right] \\
&\quad * L(y_{i1}, \dots, y_{it}) \\
&= \left[\int \prod_{s=1}^t L(d_{is} | y_{i1}, \dots, y_{is-1}, \alpha, \eta_b) \prod_{s=1}^t L(b_{is} | y_{i1}, \dots, y_{is-1}, \eta_b) f(\alpha, \eta_b) d\alpha d\eta_b \right] \left(\prod_{s=1}^t L(y_{is} | y_{i1}, \dots, y_{is-1}) \right) \\
&\equiv \left\{ \int L_i^1(\alpha, \eta_b) L_i^3(\eta_b) f(\alpha, \eta_b) d\alpha d\eta_b \right\} L_i^2
\end{aligned}$$

The first equality and second equalities follow by the law of total probability. The third equality follows because productivity is unaffected by the taste and overconfidence heterogeneity and because beliefs are unaffected by the taste heterogeneity. The fourth equality holds because, since earnings do not depend on the unobserved heterogeneity, they can be taken outside the integral. The fifth equality follows because (a) future earnings are not observed when a worker decides to quit and (b) quit decisions are independent of reported subjective beliefs conditional on the overconfidence unobserved heterogeneity. The sixth equality follows because (a) since the ϵ shocks are iid, the decision to quit is conditionally independent of all prior decisions to quit (given the earnings realizations and the unobserved heterogeneity) and (b) reported subjective beliefs are conditionally independent of past reported subjective beliefs conditional on productivity and the belief heterogeneity. In the seventh equality, I define the part of the likelihood due

⁸³Similar derivations can be found in [Rust \(1987\)](#) and [Stange \(forthcoming\)](#).

to the quitting decisions as $L_i^1(\alpha, \eta_b)$, the part due to the earnings realizations as L_i^2 , and the part due to subjective beliefs as $L_i^3(\eta_b)$.

Once the likelihood function has been derived, it is important to give an expression for $L(y_{is}|y_{i1}, \dots, y_{is-1})$. This is done as follows:

$$\begin{aligned} f(y_{i1}) &\sim N(\eta_0, \sigma_0^2 + \sigma_y^2) \\ f(y_{is}|y_{i1}, \dots, y_{is-1}) &\sim N((1 - \gamma_{s-1})\eta_0 + \gamma_{s-1}\bar{y}_{is-1}, \Omega_{s-1}) \text{ for } s > 1 \end{aligned}$$

and where $\gamma_s = \frac{s\sigma_0^2}{s\sigma_0^2 + \sigma_y^2}$ and $\Omega_s = \frac{\sigma_0^2\sigma_y^2}{s\sigma_0^2 + \sigma_y^2} + \sigma_y^2$.⁸⁴

⁸⁴This follows by applying the standard formula for the conditional density for a multivariate normal distribution: $X_1|(X_2 = x_2) \sim N(\mu_1 + \Sigma_{12}\Sigma_{22}^{-1}(x_2 - \mu_2), \Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21})$.