Learning, Persistent Overconfidence, and the Impact of Training Contracts

Mitchell Hoffman*
University of California, Berkeley

Job Market Paper
September 2011

Abstract

Since workers may quit, firms will under-invest in training. This paper studies in detail a common mechanism used to overcome this hold-up problem: training contracts, where firms provide training, but fine workers for leaving within some period of time. I study training contracts in the context of the US trucking industry where they are widely used. I document that firms that train almost ubiquitously use training contracts, and, exploiting a pair of plausibly exogenous contract changes implemented in different parts of a leading trucking firm at different times, I show that training contracts significantly affect turnover. Given the importance of worker beliefs in theories of turnover, I analyze high-frequency data on worker productivity beliefs. Subjective productivity beliefs are highly informative. However, the data also reveal that workers are persistently overconfident with only gradual learning. Worker overconfidence raises important issues about the welfare consequences and optimal design of training contracts. To examine these issues, I develop a structural model of belief formation and turnover. A learning model with biased beliefs can parsimoniously account for many key features of the data. Counterfactually restricting workers’ ability to take on training contracts may increase welfare for very overconfident workers, but would significantly reduce average worker welfare. Alternatively, reducing worker overconfidence would raise worker welfare, but would also reduce worker retention and firm profits. Overall, training contracts appear to increase the profitability of training; however, even when firms use training contracts, training may not be profitable unless workers are also overconfident.

*PRELIMINARY- DO NOT CITE OR CIRCULATE. Address: 549 Evans Hall #3880, Berkeley, CA 94720, e-mail: hoffman@econ.berkeley.edu. I am indebted to David Card, Stefano DellaVigna, Steve Tadelis, and especially John Morgan for their advice and encouragement. I am extremely grateful to Stephen Burks for sharing his data with me and for his continuous support and advice throughout this project. I also thank Firm A and Firm B for sharing data with me, as well as the numerous trucking industry managers and drivers who shared their insights with me. Thanks also to Ben Handel, Ben Hermalin, Ken Judd, Pat Kline, Botond Koszegi, Jonathan Leonard, Ulrike Malmendier, Don Moore, Enrico Moretti, Denis Nekipelov, Matthew Rabin, Jesse Rothstein, Felix Vardy, and seminar participants at Berkeley, RAND, University of Chicago, the Washington University Graduate Conference, the North American Summer Meeting of the Econometric Society, and Firm A for helpful comments. Christina Chew, Sandrena Frischer, Will Kuffel, Anmol Lingnurkar, and Irina Titova provided outstanding research assistance. Financial support from the National Science Foundation IGERT Fellowship and the Kauffman Foundation is gratefully acknowledged.
1 Introduction

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. This type of hold-up has been blamed by some for low levels of formal training in the US relative to other countries with lower labor turnover (e.g. Blinder and Krueger (1996)). The canonical solution developed by Becker (1964) is for workers to pay for training themselves. Despite this, however, growing evidence shows that a significant amount of training is paid for by firms.\(^1\) If workers are credit-constrained, for example, Becker’s solution may no longer be feasible.\(^2\)

An alternative to workers paying for training is to write contracts which solve the worker’s inability to commit. 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 they leave early, they must pay back their training costs. Training contracts of this form are used for many workers including truckers, policemen, firefighters, paramedics, electricians, salesmen, nurses, pilots, flight attendants, metalworkers, mechanics, securities brokers, and firm-sponsored MBAs, but have received limited attention from economists.\(^3\) How do training contracts affect worker turnover, worker selection, and firm training? How should firms design training contracts and how should they be regulated?

To make headway on these questions, I make use of rich data and contractual variation from the US trucking industry, where I document that training contracts are frequently used. I use personnel data from two large firms, but focus mostly on one leading firm, which I refer to as Firm A, at which there is plausibly exogenous contractual variation, as well as panel survey data on worker subjective beliefs. At Firm A, training was initially provided free of charge with no contractual obligations. In the early 2000s, the firm happened upon the idea that a training contract might improve retention, as well as help the firm recover some of the training costs from workers who leave. A 12-month training contract was created. However, 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 the amount owed by the worker decreasing over time. Again, the contract was phased in gradually. I exploit the staggered timing of these two different contracts to estimate that the 12-month and 18-month contracts reduce quitting by 10 to 20 percent relative to a situation with no training.

\(^{1}\)See e.g. Acemoglu and Pischke (1999a) and Cappelli (2004).

\(^{2}\)There are many reasons besides credit constraints that firms will pay for training including labor market fractions, information asymmetries, and screening benefits (Acemoglu and Pischke, 1999a). Further discussion is given in Section 2 and 3.

\(^{3}\)See Kraus (2008) and Kraus (1993) for many of these examples, as well as a review of legal issues surrounding training contracts. In empirical 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.
contract. The effects appear to be primarily driven by incentives instead of selection.

In Jovanovic’s (1979) canonical theory of turnover, worker productivity beliefs play a critical role. Thus, a big advantage of the Firm A data is that weekly panel data on worker subjective productivity beliefs is available for a large subset of drivers. I analyze this data so as to better understand worker turnover in the presence of training contracts. I show that these beliefs have substantial empirical content. Workers’ beliefs about future productivity significantly predict quitting and future productivity, and there is significant heterogeneity in beliefs across workers. In addition, the data shows that workers are significantly overconfident about their productivity. On average, workers begin over-predicting their productivity by roughly 25%. This overconfidence decreases over times, but persists throughout the two year panel.

Overconfidence raises important considerations for the welfare consequences of training contracts. While training contracts are legally permissible within some guidelines, some have argued that training contracts are exploitative and amount to a mild form of indentured servitude.\textsuperscript{4} Arguments that workers should be legally restricted from entering into training contracts seem to fly in the face of standard economic reasoning; providing an additional option for financing training seems unlikely to hurt workers. However, if workers are systematically biased in their assessment of their ability at a job, the argument is less clear.\textsuperscript{5} 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 been rational. While potentially harmful for workers, worker overconfidence may benefit firms. Worker overconfidence may increase the profitability of training both by making workers more likely to sign up for training contracts and by making workers more likely to stay.

To better understand observed behavior and to quantitatively assess these considerations, I develop a dynamic model of turnover and belief formation. After training, workers solve an optimal stopping rule dynamic programming problem of when if ever to quit the firm. In many 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 the canonical work of Jovanovic (1979). Using weekly productivity realizations, workers form expectations of their future productivity and earnings, and use this to decide whether or not to quit. Although workers update their beliefs in response to new information in my model, I do not impose that worker beliefs be fully rational. In doing so, my model nests (a simplified version of) the Jovanovic model as a special case.

\textsuperscript{4}These arguments 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-LA 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 US Court of Appeals. See Gordon v. Oakland. In Heder v. City of Two Rivers, a firefighter argued his training contract constituted “involuntary servitude.”

\textsuperscript{5}A growing legal literature discusses how the law of contracts should be shaped by behavioral biases, e.g. Kronman (1983), Eisenberg (1995), and Jolls and Sunstein (2006).
I then structurally estimate the model. The model replicates several key features of the data including the quit-tenure curve, the productivity-tenure curve, and the belief-tenure curve. Over-confidence plays a key role. First, overconfidence helps fit the observed pattern of beliefs. Second, the degree and form of overconfidence from the belief data helps bring the model prediction and data on quitting patterns into closer alignment. Learning is also important. In a model with learning, because productivity is initially unknown, workers have an incentive to postpone quitting in order to learn how productive they will be. I show that such a model can generate the upside-down U quit hazard observed in the data. This quitting pattern is consistent with a learning model of quitting, but is not consistent with a model where workers already know their productivity, or one where workers do not know their productivity but fail to learn from additional signals. Learning is also important for explaining the belief-tenure curve, as it helps rationalize why the level of over-confidence decreases over time. Estimating the model off of 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 regimes.

Having estimated the model, I use the estimates for counterfactual simulations. First, I simulate a government ban on training contracts. While such a ban is beneficial on net toward a small percentage of the population that is extremely overconfident, I find that a ban would substantially reduce overall total welfare. I next consider a policy that would reduce workers’ overconfidence. Such a policy may be more attractive since it potentially helps out heavily biased workers while not disadvantaging workers who are not biased. I show that this policy would significantly improve worker welfare, though it would also decrease firm profits and worker retention. I also study optimal training contract for firms, and analyze how contracts would optimally adjust in response to an intervention that reduced worker overconfidence.

The results in my paper are specific to a particular industry, and as such, there are questions of external validity. However, there are several reasons why long-haul trucking is an interesting context for studying the effects of training contracts. First, training contracts are a central mechanism by which general training is provided for truckdrivers, a large occupation employing 3.2 million Americans. Second, and more importantly, trucking provides an ideal setting for examining training contracts in the context of Jovanovic’s (1979) model of turnover where workers gradually learn about their productivity or job match. Long-haul truckers are typically paid a piece rate proportional to their productivity (the number of miles they drive per week). Unlike in many other industries, productivity in trucking is easily measurable, and is accurately recorded.

---

6Whether 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 Hoffman (2011b).

7Several other papers use computational methods to compute optimal contracts when there are several different forces. For example, Armstrong et al. (2010) computationally analyze optimal compensation contracts with both moral hazard and adverse selection.

8See Section 3 below for information on the extent of training contracts in trucking.
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 affect worker turnover, estimating the effects using 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.\(^9\) While Chiappori and Salanie (2003) argue that natural experiments may help researchers circumvent such endogeneity problems in studying contracts, relatively few such studies exist. Second, I provide long-term field evidence on overconfidence and quantify its welfare impacts for workers. To do so, I develop a structural learning model augmented with heterogeneous and biased beliefs. 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.

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,\(^10\) which is critically surveyed in Acemoglu and Pischke (1999a). Becker (1964) shows that workers should pay for training to alleviate hold-up. However, firms may pay for training for several reasons including informational asymmetries, search frictions, partial firm-specificity of training, and wage compression due to minimum wages or unionization (Acemoglu and Pischke, 1999a), or also because of worker credit constraints. The closest part of the literature on firm-sponsored training to my paper is that on

\(^{9}\) For 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 (what I will show to be) plausibly exogenous contract changes *within different segments of a single firm over time*, I provide credible estimates of causal effects.

tuition reimbursement. Larger firms (those with 50 or more workers) spent $2.8 billion on tuition reimbursement in 1994, according to the Survey of Employer Provided Training, 1995, and it is estimated that firms spent $10 billion in tuition reimbursement in 2003 (Manchester, 2009). In a recent sample of MBA students, Manchester (2011) found that 87% were on 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 to stay with a firm. Other recent papers on tuition assistance include Cappelli (2004), Gicheva (2009), and Balmaceda (2005). 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. 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. In my study, I analyze overconfidence using weekly data over two years. Workers receive frequent signals and are making guesses about their productivity, an individually-important piece of information. I analyze how overconfidence affects turnover using reduced-form and structural approaches, and I also analyze structurally how contractual design is shaped by workers’ overconfidence.

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 also been used theoretically and empirically to analyze wage growth (Harris and Holmstrom, 1982), 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 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 in North Carolina. My largest point of departure with these papers is that I allow for both generalized and non-rational learning. Specifically, I

11 Recent papers on overconfidence in economics include Burks et al. (2010), Eil and Rao (2011), Benoit and Dubra (forthcoming), Mobius et al. (2010), and Hoffman (2011a).
12 Moreover, the goal of my paper is not simply to document the existence of overconfidence, but also (and more importantly) to analyze its implications for market behavior.
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 IO papers, Goettler and Clay (2010) and Grubb and Osborne (2011), estimate biased learning models of cellular phone service demand. In my model, possible learning biases are identified through high-frequency subjective beliefs, whereas in Goettler and Clay (2010) and Grubb and Osborne (2011), biases are identified through contractual choices. Because of the richness of the belief data, I am able to estimate heterogeneity in people’s belief biases, e.g. some people are well-calibrated, some are moderately overconfident, some are very overconfident, etc.

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. 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.

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. Becker’s solution is for the worker to pay for training herself, 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. However, after training, the firm requires that the worker 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.

---

14 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.

15 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.

16 For an excellent discussion of the literature on subjective beliefs, see Manski (2004).
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.\textsuperscript{17,18}

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, 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 be beneficial to firms who use training contracts. As I show in the Appendix, overconfidence may make training more profitable for firms. Overconfidence may make it easier to get workers to sign up for training contracts and may make it easier to retain workers once they have begun.\textsuperscript{19}

### 3.2 Legal Issues Regarding Training Contracts

This section draws primarily on the excellent review articles of Kraus (2008) and Kraus (1993). Courts in the US and abroad have generally ruled that training contracts are legally permissible, arguing they serve the public good by promoting investment in worker training. 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

\textsuperscript{17}To see why, note that if a particular quitting decision is efficient, but not advantageous for the worker given the training contract, the firm can simply reduce the training contract to allow the worker to quit. Conversely, if it is socially optimal for the worker to stay, but individually advantageous for the worker to quit, the firm can bribe the worker to stay. The level of the bribe may be affected by the training contract, but the level of turnover will not be.

\textsuperscript{18}In 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 may fail to hold, and shows empirically that job security provisions do indeed affect firm firing.

\textsuperscript{19}In 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.
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 be no larger than the cost of training for firms. However, defining the actual “cost” of training is a difficult matter (for example, 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. 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.

3.3 Background on the US 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. Truckload drivers are usually paid by the mile (a piece rate) (Belzer, 2000). 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.

---

20 For 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 salesmen trainee did not fulfill three years of service, the court deemed the contract to be enforceable.

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

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

23 For an analysis of productivity in trucking, see Hubbard (2003).

24 In 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 TL 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).

25 For more information on the trucking industry, see, for example, Burks et al. (2011).
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).26

Truckdriver hours are legally restricted per the federal Hours-of-Service Regulations. Truckdrivers can work up to 60 hours per week.27 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.28 Factors such as weather, traffic, and variable loading/unloading time create substantial within-driver mileage variation. Weekly miles, my measure of driver productivity, thus reflects both driver decision-making as well as factors that drivers cannot 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 US. 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 train-

---

26 A 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.

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

28 One important factor is whether drivers arrive to a location on-time. Drivers who arrive late may have to wait around for 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.
ing 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 6 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.

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 US trucking company. Firm A provides CDL training to thousands of new drivers throughout the United States at several training schools. Prior to 2001, all training was provided at no cost to the worker with no contractual obligation.

In late 2000, several managers at the company began to discuss the idea of possibly implementing a training contract. The company had never used a training contract before. The primary motivation for implementing a contract, according to senior executives at the company, was to help increase retention, with a secondary motivation being to help recover costs. According to the Director of Driver Training, management had not previously been aware of the option of training as a “possible lever to pull,” but gradually came around to the idea of a contract as a means of possibly reducing turnover. In order to implement the contracts, it was necessary in each state

\[ TRAIN = 0.13(0.13) + 0.80(0.20) * CONTRACT + COMPANYFE + YEARFE \] (1)

Thus, when companies use a training contract, they are 80 percentage points more likely to train then when they do not use a training contract.

\(^{29}\) I can also place the result in a regression framework, using the panel data on contracts across firms. I regress whether a firm provides CDL training on whether the company is using a training contract, as well as firm fixed effects and year fixed effects. The result is as follows (standard errors are clustered by firm to allow for autocorrelation of the error term within firms):

\[ TRAIN = 0.13(0.13) + 0.80(0.20) * CONTRACT + COMPANYFE + YEARFE \]

\(^{30}\) In a regression of CDL training on log 2008 revenue, the coefficient on log 2008 revenue is 0.16 \((p = 0.06)\).

\(^{31}\) Management was initially uncertain how recruits would take to the idea of a training contract. As a Senior Vice
to have the contract certified by the state. 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 put in use as the certification process dragged on indefinitely. This penalty for leaving varied slightly by training school and was between $3,500 and $4,000. The contract applied for both quits and fires.

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. According to a Senior Vice President, the decision was reached after a long conversation about the costs and benefits of making a change, and included advice from an economist. Again, the contract was changed at different training schools at different times, with the times determined by when the contracts were approved by the relevant state boards. Under the new 18-month contract, the amount owed was initially around $5,250, and was reduced by $67.50 for each week of service. Of the $67.50 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 her $12.50 payments over 78 weeks in the form of a single bonus payment. Both the adoption of the 12-month contract and of the 18-month contract were made without additional changes in the drivers’ wage.

**Enforcement.** 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 a driver did not pay promptly, they were referred to a collection agency. Though comprehensive data on collection is not available, limited data from late 2004 reveals a fairly aggressive collection policy. Firm A collected roughly 20% of the amount owed before referring the accounts to collections. The collection agencies then collected an additional 5 to 10 percent. When drivers failed to pay, credit

---

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

33 The President put it, the contract “was about trading uncertain costs versus uncertain benefits” and that he thought “it would be worthwhile from a retention perspective.”

34 The 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.

35 According 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. I focus most of the analysis in this paper, particularly the structural analysis, on quits because quits are roughly 4 times more prevalent than fires in the data. I show reduced form evidence, however, on the impact of the training contracts on both quits and firms.

36 Firm 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.
agencies were notified.

4.2 Data

The data from Firm A is highly advantageous for an analysis of the effects of training contracts and turnover due to its large size and high frequency of observation. The data contains 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.\(^{37}\) For each driver, there is also basic demographic information, information about a driver’s boss, and information about a driver’s work environment.

Very detailed data is 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).\(^ {38}\) Subjective belief data about next week’s productivity is available only for drivers in the data subset.\(^ {39}\)

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 difference in characteristics across the regimes, but some of these reflect inter-school demographic differences (given that contracts were changed at different schools at different times).

The lower panel of Table 1 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.\(^ {40}\) One striking characteristic of the drivers is their low 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 United States general population is 723. While only 7% of the United States

---

\(^{37}\)Drivers 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).

\(^{38}\)Further 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 driver subset.

\(^{39}\)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.

\(^{40}\)Truckdrivers 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.
4.3 Do Training Contracts Affect Quitting?

To analyze the effect of the training contract on quitting, I first plot survival and hazard curves under the different contractual regimes. Figure 1 plots survival curves for the different contractual regimes. 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 contractual regimes. For drivers with the 12-month contract, the hazard is decreasing until the 52-week mark where there is a large spike in the hazard rate. There are also small bumps at the 52-week mark under the no contract and 18-month regimes, but they are smaller.

To more closely quantify these effects, I estimate proportional hazards models of quitting and firing. Every week, a driver faces some risk of quitting and being fired, which is influenced by her characteristics, including whether or not she has a training contract. Specifically, I estimate hazard models of the form:

\[
\log(h_{it\tau cs}) = \alpha_t + \beta_1 \cdot 12MCONTRACT_{sc} + \beta_2 \cdot 18MCONTRACT_{sc}
\]

\[
+ \beta_3 \cdot UNEMP_{st} + \beta_4 \tilde{y}_{it} + \gamma_{\tau} + \delta_c + \theta_s + X_i \lambda + \epsilon_{it\tau cs}
\]

where \(h_{it\tau cs}\) is the quit propensity of a driver \(i\) with \(t\) weeks of tenure in month \(\tau\) who is part of cohort (year of hire) \(c\) who attended training school \(s\); \(UNEMP_{st}\) is the unemployment rate in state \(s\) at time \(\tau\); \(\tilde{y}_{it}\) is average earnings to date; \(\alpha_t\) is a fixed effect for tenure \(t\); \(\gamma_{\tau}\) is a time fixed effect for month \(\tau\); \(\delta_c\) is a fixed effect for year of hire \(c\), \(\theta_s\) is a school fixed effect; and \(\epsilon_{it\tau cs}\) is an error. The coefficients \(\beta_1\) and \(\beta_2\) are the main ones of interest, and capture the effects of the contracts on the hazard of quitting. 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 -0.17 and -0.10, respectively.

That is, the 12-month and 18-month contract decrease the probability of quitting by roughly 17 and 10 percent. A percentage point increase in state unemployment is estimated to reduce quitting

---

41The drivers analyzed here have credit scores that seem similar to the car loan applicants analyzed in Adams et al. (2009).

42In discussions with Firm A, managers 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.

43For these regressions, I present the robust standard errors. Clustering by training school, I have a small number of clusters, and the clustered standard errors are smaller than the robust standard errors. I have also calculated standard errors using a block bootstrap. As a robustness check, I have also performed all regressions using OLS. The results are very similar. For the OLS results, I have also calculated standard errors using the parametric Moulton
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 $\beta_1$ and $\beta_2$ remain similar or become larger.

The interaction effects in Table 2 reveal when the impacts of the training contracts are being felt. 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 how the effects of the contracts varied with tenure, I ran OLS regressions of quitting on interactions of the contracts with tenure blocks:

$$q_{itrcs} = \sum_{r=1}^{8} \beta_{1r} \ast 12MCONTRACT_{sc} \ast TENUREQUARTER_{r}$$

$$+ \sum_{r=1}^{8} \beta_{2r} \ast 18MCONTRACT_{sc} \ast TENUREQUARTER_{r}$$

$$+ \beta_3 \ast UNEMP_{st} + \beta_4 \bar{y}_{it} + \eta_t + \gamma_r + \delta_c + \theta_s + X_i \lambda + \epsilon_{itrcs}$$

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. Standard errors are clustered by driver. 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 changes in quit patterns in cohorts near in time to when the contract was changed at the different training schools. This suggests 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 for 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:
\[ \text{Quit}_{5378}^{ics} = \alpha_s + \beta_c + \sum_{j=T}^{T} \theta_j D_{sc}^j + X_i \lambda + \epsilon_{ics} \]  

where \( \text{Quit}_{5378}^{ics} \) is a dummy for whether worker \( i \) quits in weeks 53-78 (conditional on having stayed through week 52), \( \alpha_s \) and \( \beta_c \) are school and year of hire fixed effects, \( D_{sc}^j \) is a dummy given below, and \( \epsilon_{ics} \) is an error. \( D_{sc}^j \) is a dummy for whether cohort \( c \) (those starting work in quarter \( c \)) at training school \( s \) are \( j \) periods from the introduction of the 18-month contract; formally, \( D_{sc}^j = 1(c - e_s = j) \), 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 \( T = -3 \) and \( T = 9 \) (\( T = -7 \) and \( T = 4 \)). Further, I “bin up” the end points by including dummies for the event time being less than \( T \) or greater than \( T \).\(^{44}\)

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 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

Endogenous Contract Changes. The above coefficients were estimated assuming that the contractual regime is exogenous to other factors which may affect quitting. For example, if contracts were implemented earlier in areas where the turnover problem was expected to be more acute, then I will be underestimating the effects of the training contracts on quits and fires. Alternatively, if it was easier for the company to implement the training contract in areas where the turnover problem was less severe, than I will have overestimated the relevant effects. Discussions with the firm indicate this is unlikely to be a concern. According to the firm, the fact that the training contracts were approved more quickly in some states than in others was mostly idiosyncratic, perhaps reflecting differences in the speed of state bureaucracy. A possible exception to this is the training school in California. California is generally viewed as being strongly pro-employee, and the 12-month contract in California was postponed indefinitely. Even if the contract’s slow introduction in California was not random, however, it seems unlikely to be related to the factors determining turnover.

Worker Sorting into Schools. Another potential confound to identification would be worker sorting into training schools. For example, a worker who believed she had a high chance of quitting

\(^{44}\)Note that I restrict to the sample of drivers who eventually exit the company.
might prefer to attend a training school that did not have a training contract. This is unlikely to be an issue in practice because drivers nearly always attend the training school closest to their home address, e.g. new drivers from California attended the training school in California, those in the Midwest attended a training school there, etc. In the data, driver zip code and state are an extremely strong predictor of the driving school a driver attends.

**Time-Varying Contract Enforcement.** Could it be that the contract was enforced differently depending on the worker’s tenure? Under the 12-month training contract, a driver who left one week before the end of her contract was technically responsible for the same amount as a driver who left after several weeks. This possibility does not threaten identification of the overall effects of the contract, but it would seem a threat to interpretation of the different temporal paths of quitting and firing under the different contracts. However, both a Senior Vice President and a training manager said that this was not an issue, and that the contract was enforced generally irrespective of worker’s tenure.\(^{45}\)

### 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, 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 the training contracts affect the rate of firing. If the training contract induced better workers to work at Firm A, one would expect this to lead to a decrease in the rate of firing. Table 3 analyzes the effect of the contracts on firing rates. None of the effects are 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 4, there is not much 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

\(^{45}\)A 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.
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.46

These tests provide support for some selection due to the training contracts, but the effects
seem 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 limited?
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.47 Another possibility is that the contract may not have been
salient for some reason to drivers when they signed up for the job.48 A third possibility may be that
selection is multi-dimensional, which has been observed, for example, in health insurance contracts
(Finkelstein and McGarry, 2006). In my setting, one can imagine that workers are 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. Indeed,
as is shown in Section 5, more productive workers are indeed significantly less overconfident about
their ability.

46This test is inspired by the test for selection in Lazear (2000). Lazear (2000) 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.

47In my structural model, I will make the assumption that workers and firms do not have private information about
the worker’s productivity before she starts work.

48This seems unlikely to be the case, as a discussion of training contracts was a mandatory part of interviews at
Firm A.
4.5 Worker Learning

A central argument in this paper is that quitting decisions reflect 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 provides confirmatory evidence on this implication. Figure 5 compares the average earnings per week of drivers who make it to that week and then quit versus drivers who make it to that week and then do not quit. Quitting drivers receive lower average earnings in prior weeks than non-quitting drivers.

This effect is quantified in Table 2. As can be seen, an increase in past average earnings is associated with a reduced hazard of quitting. Higher worker productivity is also associated with a lower chance of being fired. The evidence is consistent with a learning-based model of turnover, but that is not the only model it is consistent with.\(^{49}\) To better get at whether a learning model best characterizes quit patterns, I turn to a structural model.

5 Worker Beliefs

Worker productivity beliefs are key in theories of turnover. In this section, I examine whether incorporating subjective beliefs can help better predict productivity and turnover under training contracts.\(^{50}\)

Drivers in the data subset were asked each week to predict their miles in the following week. Every week, drivers were 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.\(^{51}\) 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

\(^{49}\)For example, it may be that drivers know their underlying productivity, but productivity is subject to shocks. Suppose further that productivity shocks are correlated with outside family shocks. In this case, lower productivity workers will be more less likely to quit. But the reason is not because of learning, but because of the family shock.

\(^{50}\)I focus here on the predictive power of beliefs. My companion paper Hoffman (2011b) addresses how workers form and update their beliefs.

\(^{51}\)Though the question was asked on a Wednesday, I assume for now that it was asked at the beginning of the week, and thus refers to the week ahead. Instead one could also simply take the beliefs question from the week before to count as the current week’s beginning of the week question.
survey. 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.

In Table 6, I examine whether subjective productivity beliefs help predict productivity over and beyond other predictors. Specifically, I consider regressions of the form:

\[ y_{i,t} = \alpha + \beta b_{i,t-1} + \gamma \bar{y}_{i,t-1} + X_i \delta + \epsilon_{i,t} \]  

(5)

Column 1 estimates with nothing on the right-hand side besides lagged beliefs; the estimated \( \beta \) is roughly 0.2. Once controls such as added 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 less than one for one. The coefficients on the beliefs may, however, be downward biased due to measurement error in subjective beliefs.

Table 5 reports the results of a regression of quits on productivity beliefs:

\[ q_{i,t} = \alpha + \beta b_{i,t-1} + \gamma \bar{y}_{i,t-1} + X_i \delta + \epsilon_{i,t} \]  

(6)

where \( q_{i,t} \) is a dummy for the worker quitting in period \( t \). Average earnings to date, \( \bar{y}_{i,t-1} \) 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 hundred point increase in subjective miles predicts a 6 percent decrease in the probability a worker quits. Again, measurement error is a potential concern here. 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 predictive, another basic question is whether or not they

---

52 At a different firm, Firm B, I elicited miles expectations while randomizing whether or not drivers were given financial incentives for accurate belief (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 studies using incentives for beliefs elicitation include Grisley and Kellogg (1983) and Nelson and Bessler (1989).

53 Women 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 is more productive. Later, I perform a robustness check where I use inverse probability weighting to deal with the non-random response to the question.

54 In the Online Appendix, I present IV regressions where I instrument workers’ productivity beliefs with next period’s productivity. Worker productivity beliefs significantly predict turnover in OLS regressions, but the effect is larger in the IV specifications, consistent with the presence of measurement error in the beliefs data.
are well-calibrated. Figure 6 analyzes productivity and productivity beliefs by tenure. 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. To analyze the dynamics of productivity and beliefs, I plot local polynomial regressions. These regressions are plotted in Figure 6 with standard error bars. 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 of signals, workers are still overconfident by around 150 miles per week.  

The results make substantial heterogeneity and variable 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 her 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. This heterogeneity is plotted in the lower part of Figure 6.  

Workers exhibit significant overconfidence in their beliefs about their earnings as truckdrivers. Yet, for overconfidence to reduce worker quitting in theory, the worker must be more overconfident about her current job earnings than her outside option. While this assumption is very difficult to test, I provide some suggestive evidence her that this does not appear to be the case. Drivers in the data subset were asked what their earnings would have been had they not started work with Firm A. The answer to this question was restricted to eight income ranges: $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+. I compare drivers’ response to this question to what “similar-looking” people earned in the Current Population Survey (CPS). Figure 7 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. 

---

55I interpret the question “How many miles do you expect to run next week?” as asking drivers for their mean expected miles next week. However, 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 are 1% less than than the mean miles per week). Thus, whether workers reported the mean or median expected miles seems unlikely to matter for my estimation.

56See Hoffman (2011b) for further evidence on heterogeneity.

57The 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?”
6 The Model

I develop a dynamic model of entry, quitting, and belief formation where workers learn about their productivity over time. The model is a discrete time extension of the model of 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 every week whether or not to quit her job. The problem is an optimal stopping problem; once she quits, she cannot return. The worker is paid according to a piece rate, but individual productivity is initially unknown, both to the worker and the firm. The worker’s quitting decision is based on her subjective belief about her future productivity as a truck driver. Subjective beliefs are formed based on weekly productivity realizations. The worker is forward-looking and takes into account the option-value of staying on with the firm to learn about their productivity. Workers are heterogeneous not only in their underlying productivity, but also in their priors about average productivity of truck-drivers in the population and in their taste for the job or career, and I allow for both observed and unobserved (to the econometrician) dimensions of heterogeneity. Driver’s differential priors about average productivity as a truckdriver is the source of overconfidence in the model. Drivers who believe that the average truckdriver is very productive will begin overconfident about their own future productivity (i.e. they will have biased priors). With additional productivity draws, their overconfidence diminishes.

In the basic model above, both the piece rate and the bonding contract are taken as given. Later, in Section 9, I consider optimal contract choice for the firm given the worker’s behavior.

6.1 Model Setup

Workers have baseline productivity $\eta$, which is distributed $N(\eta_0, \sigma^2_0)$. Workers are paid by a piece rate, $w_t$, that depends on their tenure. 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 $Y_t = w_t y_t$. 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 $y_1, y_2, ..., y_{t-1}$, but not their current week miles, $y_t$. Workers are assumed to be risk-neutral, and to have a discount factor given by $\delta$.

---

58I 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 has working hat are 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.

59In addition, I abstract away from the firm’s ability to fire workers.

60This is the standard pay system for the US trucking industry. For example, a trucker who does not own his own truck may receive 30 cents per mile.

61Risk neutrality is assumed in many dynamic learning models, e.g., Crawford and Shum (2005), Nagypal (2007), Stange (forthcoming), and Goettler and Clay (2010). Coscelli and Shum (2004) show that risk parameters are not
**Stay-or-Quit Decisions.** Workers make their stay-or-quit decisions every period to maximize expected utility:

\[ V_t(x_t) = \max_{d_t, d_{t+1}, \ldots} E_t \left( \sum_{s=t}^{\infty} \delta^{t-s} u_t(d_s, x_s) | d_t, x_t \right). \]  

(7)

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

\[ V_t(x_t) = \max_{d_t} E_t \left( u_t(d_t, x_t) + \delta V_{t+1}(x_{t+1}) | d_t, x_t \right). \]

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 \( \alpha \). The per-period utility from staying is assumed to be given as the sum of utility from earnings, the taste for trucking, and an idiosyncratic shock:

\[ u_t(1, x_t) = \alpha + w_t y_t + \varepsilon_t^S, \]

where \( \varepsilon_t^S \) is an iid idiosyncratic error unobserved to the econometrician (but observed by the worker) with an Extreme Value-Type 1 distribution and scale parameter \( \tau \). In the estimation, I explore several functional forms for the unobserved heterogeneity including a normal distribution and a mass-point distribution (Heckman and Singer, 1984).

If the worker quits, she may have to pay a fine associated with the training contract. Let the vector \( k \) denote the training contract, with \( k_t \) being the penalty for quitting at tenure \( t \). The utility from quitting can be written as:

\[ u_t(0, x_t) = -k_t + \frac{r_t}{1-\delta} + \varepsilon_t^Q. \]

where \( \varepsilon_t^Q \) is an iid unobserved idiosyncratic error with the same distribution as \( \varepsilon_t^S \). Note that the fraction \( \frac{r_t}{1-\delta} \) includes a time subscript, expressing that a worker’s outside option may depend on her 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

\[ V_t^S = E_t \left( u_t(1, x_t) + \delta V_t(x_{t+1}) | 1, x_t \right) \]

\[ V_t^Q = E_t \left( u_t(0, x_t) + \delta V_t(x_{t+1}) | 0, x_t \right) \]

be the value functions for staying and quitting, respectively. Using the continuation values, and the above expressions for \( u_t(1, x_t) \) and \( u_t(0, x_t) \), the choice-specific value functions can be written identified in certain classes of learning models.
as:

\[ V_t^Q = -k_t + \frac{r_t}{1-\delta} + \epsilon_t^Q \equiv V_t^Q + \epsilon_t^Q \]
\[ V_t^S = \alpha + E_t(w_t y_t | x_t) + \delta E(V_{t+1}(x_{t+1}) | x_t) + \epsilon_t^S \equiv V_t^S + \epsilon_t^S, \]

and the Bellman Equation can be re-written as

\[ V_t(x_t) = \max_{d_t \in \{0,1\}} \left( V_t^S(x_t), V_t^Q(x_t) \right). \]

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:

\[ V_t^Q = \frac{r_T}{1-\delta} + \epsilon_t^Q \equiv V_t^Q + \epsilon_t^Q \]
\[ V_t^S = \alpha + w_T \eta + \delta E(V(x') | x) + \epsilon_t^S \equiv V_t^S + \epsilon_t^S \]
\[ V(x) = \max_{d_t \in \{0,1\}} \left( V_t^S(x_t), V_t^Q(x_t) \right) \]

**Belief Formation.** In a standard normal learning model, a worker’s beliefs in period \( t \) about her productivity are given by:

\[ E(y_t | y_1, ..., y_{t-1}) = \frac{\sigma_y^2}{(t-1)\sigma_0^2 + \sigma_y^2} \eta_0 + \frac{(t-1)\sigma_0^2}{(t-1)\sigma_0^2 + \sigma_y^2} \sum_{s=1}^{t-1} y_s - a(s) s - 1 + a(t) \quad (8) \]

This expression is a weighted sum of the agent’s prior and her average productivity signals. As \( t \) increases, the agent will eventually shift all the weight to the \( \eta_0 \) term over the \( \eta_0 \) term. I augment the standard learning model in two ways. First, 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 \( \tilde{\sigma}_y \) instead of \( \sigma_y \). Second, I allow for agents to be overconfident. Instead of believing that their productivity \( \eta \) is drawn from a distribution \( N(\eta_0, \sigma_0^2) \), agents believe that the productivity is drawn from a distribution \( N(\eta_0 + \eta_b, \sigma_0^2) \). With these two assumption, an agent’s subjective expectation of her productivity, which I denote by \( E^b \) (where \( b \) stands for belief) is:

\[ E^b(y_t | y_1, ..., y_{t-1}) = \frac{\tilde{\sigma}_y^2}{(t-1)\sigma_0^2 + \tilde{\sigma}_y^2} (\eta_0 + \eta_b) + \frac{(t-1)\sigma_0^2}{(t-1)\sigma_0^2 + \tilde{\sigma}_y^2} \sum_{s=1}^{t-1} y_s - a(s) s - 1 + a(t) \quad (9) \]
If the term $\eta_b$ is greater (less) than zero, then agents exhibit positive (negative) mean bias or overconfidence (underconfidence). As more signals come in, the agents will eventually learn not to be overconfident since she will put zero weight on the $(\eta_0 + \eta_b)$ term. The speed at which this occurs, however, will be determined by $\tilde{\sigma}_y$. (Note that the additional terms will also influence the believed transition probabilities $f^b(y_{it}|y_{i1}, \ldots, y_{it-1})$.)

Accurately reporting one’s beliefs about productivity may be unfamiliar for a worker. I thus assume that reported beliefs equal subjective beliefs plus a normally distributed error. Specifically, the belief of driver $i$ in her $t$th week of tenure, $b_{it}$, is distributed:

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

**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 $y_1, y_2, \ldots, y_{t-1}$.
2. $\epsilon_t^S$ and $\epsilon_t^Q$ are realized and workers decide whether or not to quit.
3. $y_t$ is realized.

**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 $\Lambda$ is the logit function and $t$ is worker tenure in weeks. 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.

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 sitting in the passenger seat. 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:

$$r_t = r - \frac{6 - t}{5} s_0 \text{ for } t \leq 5$$

$$r_t = r \text{ for } t > 5$$

---

25

---

$^{62}$The emphasis is on applying skills learned in CDL training and learning other tricks of the trade.
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.

**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: \( x_t = (y_1, \ldots, y_{t-1}, X, w_t, k_t, \alpha, \eta_b) \), 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. For example, a person’s marital status or education could affect how easy it is for them to be away from home for several weeks in a row. To add this to the model, in the choice-specific value function for staying, \( \alpha \) is now replaced with \( \alpha + X\bar{\alpha} \). I assume that all observed characteristics such as marital status, children, gender, age, and race are constant over the time frame of the data. This assumption is made due to data limitations (variables like kids and marital status are not given on a weekly basis). Given the paper’s focus on high-frequency (i.e. weekly) decision-making and that agents in the data subset are observed for around two years, it may not be unreasonable.

**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:

\[
Pr(\text{STAY}_T|x_T) = Pr(V^S_T > V^Q_T | y_1, \ldots, y_{t-1}, X, w_t, k_t, \alpha, \eta_b) \\
= Pr(\alpha + X\bar{\alpha} + E^b(w_T y_T|y_1, \ldots, y_{t-1}) + \delta E(V(x)|x_T) + \epsilon^S_T > -k_T + \frac{r}{1-\delta} + \epsilon^Q_T) \\
= \Lambda \left( \frac{\alpha + X\bar{\alpha} + w_T E^b(y_T|y_1, \ldots, y_{t-1}) + \delta E(V(x)|x_T) + k_T - \frac{r}{1-\delta}}{\tau} \right)
\]

where \( \Lambda(x) = \frac{e(x)}{1+e(x)} \) is the logit function. To evaluate this probability, it is necessary to calculate \( E^b(y_T|y_1, \ldots, y_{t-1}) \) and \( E(V(x)|x_T) \). This expectation depends on \( y_1, \ldots, y_{t-1} \), 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 \( E^b(y_t|y_1, \ldots, y_{t-1}) = \frac{\hat{\sigma}^2 + \hat{\sigma}_y^2}{(t-1)(\hat{\sigma}^2 + \hat{\sigma}_y^2)}(\eta_0 + \eta_b) + \frac{(t-1)\hat{\sigma}^2}{(t-1)(\hat{\sigma}^2 + \hat{\sigma}_y^2)}\bar{y}_{t-1} \), the average of her past productivity is a sufficient statistic for the entire sequence \( y_1, \ldots, y_{t-1} \) (DeGroot, 1970). I show how to calculate \( E(V(x)|x_T) \) in the Appendix.

For a general period \( t \), the probability of staying is given by:
Calculating $E(V_{t+1}(x_{t+1})|x_t)$ requires integrating expectations both of future earnings and future idiosyncratic shocks, and is done formally in the Appendix.

**Entry.** In some specifications, I will also model the entry decision of workers. Workers sign up to work for the company by comparing their perceived expected value of the job with their outside option. Workers are drawn from a population of $N$ potential workers. If they sign up for the job, their expected payoff is $EV_1 + \epsilon^E$. If they don’t sign up for the job, they receive $r_1 - \delta + \epsilon^{DE}$. The two idiosyncratic shocks $\epsilon^E$ and $\epsilon^{DE}$ are distributed iid extreme value type-I with scale parameter $\tau^E$.

In addition, to sign up for the job, the worker needs find out about the job, apply for the job, and be accepted for the job. Since this search process is not the focus of the paper, I assume instead a simple reduced form for the search process. Specifically, I assume that signing up for the job costs the worker $\alpha^E$ in expected value.\(^{63}\) The probability the worker signs up for the job is thus given by

$$Pr(E) = \Lambda \left( \frac{EV_1 - r_1 - \delta - \alpha^E}{\tau^E} \right)$$

### 6.2 Alternative Models

**No Learning.** To analyze the added explanatory power of learning, I will also estimate the model with no learning. In the no learning model, drivers form expectations of their productivity using the average productivity-tenure curve for drivers at the company. They assume that their individual productivity realizations reflect random deviations from the average, with no separate information about their future ability. Drivers are still allowed to have biased priors. Formally, drivers’ subjective productivity expectations are $E_b(y_{is}|y_{i1},...,y_{is-1}) = a(t) + \eta_0 + \eta_b$. All other features of the model are the same.

### 6.3 Discussion of Model Assumptions

In the model, workers hold heterogenous beliefs about their productivity. I assume, however, that these beliefs do not affect perception of the outside option. That is, a worker who is overconfident

---

\(^{63}\)This includes the worker being rejected for the job, recruiters not responding to inquiries, etc. Because the worker is risk-neutral, it is sufficient to consider the expected cost of the search process and not consider payoffs under different search outcomes.
(underconfident) about her ability at trucking is not overconfident (underconfident) about her outside option. This is a strong assumption. However, it is not needed in order for overconfidence to have some affect on the profitability of training. As I show in the Appendix, if a worker’s perception of her current job income is more responsive to her productivity beliefs than her outside option, then firm profitability will be higher than if the worker is not overconfident. To the extent that workers are also overconfident about their outside options, 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 US do not pay piece rates. Indeed, only around 37% of US jobs use any sort of performance pay, and in the jobs that do, variable pay only comprises on average only about 4% of pay (Lemieux et al., 2009). 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.

Suppose now that the worker’s outside option is another trucking job. Assume first that the worker’s overconfidence is correlated across firms with different multiplicative values, $\eta_{b,f} = \theta_f \times \theta_b$, where $\eta_{b,f}$ is a worker’s belief bias at firm $f$. In this case, the assumption that the worker is more overconfident at the current than at her outside option appears to be testable. Specifically, in the regressions of quitting on beliefs, I showed that workers who have higher beliefs are less likely to quit (see Table 5). Alternatively, assume that the agent’s overconfidence is uncorrelated across firms, $\eta_{b,f} = \eta_b + \theta_f$. In this case, it seems likely that the worker will initially select the job at which he has the highest belief of his ability, that is, she will choose the job with the highest $\theta_f$.

7 Structural Estimation

The model is estimated using maximum likelihood.

7.1 Estimation

The likelihood for a driver observed for $t$ periods consists of the observed sequence of quitting decisions, earnings realizations, and subjective beliefs. The likelihood for driver $i$ is

---

64 The issue of whether overconfidence may also affect the value of alternative activities also arises in other empirical studies of overconfidence, e.g. Malmendier and Tate (2005).

65 In addition, performance pay is more common in white-collar jobs than in blue-collar jobs (Lemieux et al., 2009).

66 Of course, other pecuniary aspects of a job, e.g. the perceived probability of being promoted to a higher wage, may affected by overconfidence.

67 I have presented several reasons why it may be more likely for overconfidence to affect the perception of current job earnings more than the outside option. This discussion, however, is far from conclusive. As a robustness check, I can consider when workers are assumed to experience some level of their overconfidence at trucking in their beliefs about their outside option. Such robustness checks are an important item for future work.
The likelihood can be expanded as follows:

\[
L_i = L(d_{i1}, \ldots, d_{it}, y_{i1}, \ldots, y_{it}, \hat{b}_{i1}, \ldots, \hat{b}_{it}).
\]

In the last line, I define \(L_1^1(\alpha, \eta_b)\) to be the part of the likelihood due to quitting decisions; \(L_1^2\) to be the part of the likelihood due to earnings realizations; and \(L_1^3(\eta_b)\) to be the part of the likelihood from the subjective beliefs. That the likelihood can be decomposed in this way is shown formally in the Appendix. For a driver who quits in period \(t\), \(L_1^1(\alpha, \eta_b)\), \(L_1^2\), and \(L_1^3(\eta_b)\) and can be written as

\[
L_1^1(\alpha, \eta_b) = \left( \prod_{s=t}^{t-1} Pr(\text{STAY}_{is}|\mathbf{x}_{is}) \right) (1 - Pr(\text{STAY}_{it}|\mathbf{x}_{is}))
\]

\[
L_1^2 = f(y_{i1}) \prod_{s=2}^{t} f(y_{is}|y_{i1}, \ldots, y_{is-1})
\]

\[
L_1^3(\eta_b) = f(b_{i1}) \prod_{s=2}^{t} f(b_{is}|y_{i1}, \ldots, y_{is-1})
\]

with

\[
f(y_{i1}) \sim N(\eta_0, \sigma_0^2 + \sigma_y^2)
\]

\[
f(y_{is}|y_{i1}, \ldots, y_{is-1}) \sim N((1 - \gamma_{s-1}) \eta_0 + \gamma_{s-1} \bar{y}_{is-1}, \Omega_{s-1}) \text{ for } s > 1
\]

\[
f(b_{i1}) \sim N(\eta_0 + \eta_b, \sigma_b^2)
\]

\[
f(b_{is}|y_{i1}, \ldots, y_{is-1}) \sim N((1 - \gamma_{s-1}^b) (\eta_0 + \eta_b) + \gamma_{s-1}^b \bar{y}_{is-1}, \sigma_b^2) \text{ for } s > 1
\]

and where \(\gamma_s = \frac{s \sigma_y^2}{s \sigma_0^2 + \sigma_y^2}, \Omega_s = \frac{s \sigma_0^2 \sigma_y^2}{s \sigma_0^2 + \sigma_y^2} + \sigma_y^2\), and \(\gamma_s^b = \frac{s \sigma_y^2}{s \sigma_0^2 + \sigma_y^2}\).

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:
\[ L = \prod_i \int L_1^i(\alpha, \eta_b)L_2^i(\eta_b)f(\alpha, \eta_b)d\alpha d\eta_b \]
\[ = \prod_i \left( \int L_1^i(\alpha, \eta_b)L_2^i(\eta_b)f(\alpha, \eta_b)d\alpha d\eta_b \right) L_3^i. \]
\[ \log(L) = \sum_i \log \left( \int L_1^i(\alpha, \eta_b)L_2^i(\eta_b)f(\alpha, \eta_b)d\alpha d\eta_b \right) + \sum_i \log (L_3^i). \]

When the unobserved heterogeneity is assumed to take a mass-point distribution, the log-likelihood can be written as a simple sum. When the unobserved heterogeneity (either taste or overconfidence) is normally distributed, integration is done by Gaussian quadrature with 10 nodes.

### 7.2 Identification

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

**Productivity parameters.** The productivity parameters \( \sigma_0, \sigma_y, \) and \( \eta_0 \) are identified primarily by the productivity data. \( \sigma_0 \) reflects the degree of permanent productivity differences across individuals whereas \( \sigma_y \) reflects differences within individuals in productivity. The parameter \( \eta_0 \) reflects mean average ability of workers in the population.

**Taste heterogeneity.** The taste heterogeneity parameters are identified based off of 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 would be widespread unobserved taste heterogeneity.

**Belief parameters.** The standard deviation of beliefs, \( \sigma_b \), is identified by how much subjective expectations differ from the mathematical expectation of future productivity. The greater the variation in subjective from mathematical expectations, the greater is \( \sigma_b \). The believed standard deviation of productivity shocks, \( \tilde{\sigma}_y \), 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 \( \tilde{\sigma}_y \) will be. Likewise, the faster that agents’ initial overconfidence in subjective beliefs begins to disappear, the smaller that \( \tilde{\sigma}_y \) will be. The belief heterogeneity is identified based off of 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, \( \tau \), 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. The skill gain parameter, $s_0$, is identified based on turnover levels during the first five weeks when workers are not being paid a piece rate.

### 7.3 Implementation

To solve the dynamic programming problem numerically, I discretize productivity into $K$ bins. In my baseline estimation, I let productivity range in increments of 100 from 100 to 4,000 miles per week, i.e. $K = 39$. Transitions between earnings states are given by:

$$\Pr(y^k_s | y_1, \ldots, y_{s-1}) = \Phi\left(\frac{y^k_s + 0.5 \times kstep - E(y^k_s | y_1, \ldots, y_{s-1})}{\sqrt{\Omega_{s-1}}}\right) - \Phi\left(\frac{y^k_s - 0.5 \times kstep - E(y^k_s | y_1, \ldots, y_{s-1})}{\sqrt{\Omega_{s-1}}}\right)$$

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, $\delta$, is assumed rather than estimated. In my preferred specification, I take $\delta = 0.9957$, corresponding to an annual discount factor of 0.8.

A few other points are worth noting. First, I am assuming that drivers act as if the contract is perfectly enforceable. Second, I report most results here without including time-invariant covariates like education and age. Third, the data contains 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

---

68 As a sensitivity check, I have also estimated with finer and coarser discretizations, as explored for example in Rust (1987), and the results are mainly similar. I have also estimated using linear interpolation instead of discretization and the results are similar.

69 This is similar to the transition probabilities in Stange (forthcoming), except I assume a normal learning model, whereas Stange (forthcoming) assumes a more general learning model, and thus uses a slightly different formula. See also Rust (1996).

70 I have experimented with a broad range of discount factors in sensitivity analysis. Model fit appears best 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 in other analyzing dynamic choices of blue-collar or low-income workers (e.g., Paserman (2008), Fang and Silverman (2009), and Warner and Pleeter (2001)).

71 As 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.

72 I 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.
decision) are given by the prior week’s average earnings to date.

8 Structural Results

Table 7 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. 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 \( \frac{t\sigma_y^2}{t\sigma_y^2 + \tilde{\sigma}_y^2} \). After 20 weeks, the worker will place weight 0.31 on her signals, whereas if \( \tilde{\sigma}_y = \sigma_y \), she would place weight 0.77 on her signals.

Column 3 estimates allowing for heterogeneity in people’s belief bias. There is again a considerable improvement in the log-likelihood. The data reveals 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. As one manager put it, “Trucking is not for everyone.”

The fit of the model is assessed graphically in Figure 10. The quit hazard-tenure profile, the productivity-tenure profile, and the beliefs-tenure profile observed in the data are plotted using an 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 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.

\[^{73}\] For 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.
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.\(^{74}\) 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.

9 Counterfactual Simulations

The ability to perform counterfactual simulations is an attractive feature of structural modeling. My goal is to assess the quantitative importance of training contracts and biased beliefs, as well as to analyze potential firm or government policies.

9.1 Profits Under Different Contracts

I first assess how different training contracts affect profits by simulating worker behavior under the three observed training contracts. I use two measures of firm profits: profits per worker and profits per truck.\(^{75}\) Average profits per worker is defined as average profits brought in from a worker during her time with the company. Implicit in such a formulation is that when a worker quits, she is not replaced.

\[
\pi(k) = \text{Trucking Profits} + \text{Training Contract Penalties} - \text{Training Costs} \tag{11}
\]

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

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), \(\theta\) 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

\(^{74}\)Chi-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.

\(^{75}\)See also Bojilov (2011) for similar profit formulas in a different context.
the opportunity cost of the truck), and $T_C$ is training cost per worker. I assume values for $P$, $mc$, $\theta$, $FC$, and $T_C$ based on consultation with Firm A.\footnote{Specifically, I assume that $P = \$1.80$ per mile, $mc = \$1.20$ per mile, $\theta = 0.3$, $FC = \$475$ per week, and $T_C = \$2,500$. 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.}

Profits can also be defined in terms of profits per truck. In this formulation, when a worker quits, she 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:

$$\pi = \sum_{t=1}^{\infty} \delta^{t-1} \left[ (1 - Q_t)(P - w_t - mc)y_t - FC) + Q_t (-TC + \theta k_t + \pi) \right]$$ (12)

which can be re-arranged to yield

$$\pi = \frac{\sum_{t=1}^{\infty} \delta^{t-1} \left[ (1 - Q_t)(P - w_t - mc)y_t - FC) + Q_t (-TC + \theta k_t) \right]}{1 - \sum_{t=1}^{\infty} \delta^{t-1}Q_t}$$ (13)

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 training contracts increase the profitability of training for firms and that Firm A may have increased profits by making its contractual changes.

### 9.2 Restricting Choice

If workers are well-calibrated about their productivity, then allowing workers to take on training contracts should improve welfare. 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 workers are restricted from being able to sign up for training under training contracts.

To assess the welfare consequences of restricting training contracts, I compare worker’s realized average utility in trucking with the alternative where they receive their outside option in all periods. Since workers have biased beliefs, average utility differ from the first period expected value function. To calculate actual utility, I simulate 40,000 trucking careers, and sum over earnings, taste for trucking, and idiosyncratic shocks. When drivers quit, they are assumed to receive the outside option thereafter.

Table 11 lists worker’s perceived utility of trying trucking, their actual average utility of trying trucking, and the value of the outside option. Despite workers being overconfident, actual average
utility is significantly higher than the outside option. Thus, banning training contracts would substantially reduce worker welfare. The welfare effects would vary substantially based on an individual’s overconfidence. Consider the two type overconfidence model estimated in column 3 of Table 7. For the vast majority of people, whom I refer to as the “low overconfidence,” types, the ban significantly decreases welfare. However, for the 6% of the population with a very high level of overconfidence, a ban increases welfare.

My preferred interpretation of this counterfactual is as a quantitative assessment of two economic forces: the value of choice versus the value of protecting people from poor decision-making. The result suggest that the value of choice is greater in this context.\textsuperscript{77}

9.3 Debiasing: Reducing Worker Overconfidence

If banning training contracts is not welfare-enhancing, an alternative policy might be to reduce workers’ overconfidence, which I will refer to as debiasing. I examine counterfactually how reducing overconfidence affects workers’ quitting and entry decisions; firms’ contractual choices; and worker welfare and firm profits. This illustrates the importance of overconfidence in my model and could also be viewed as a potential public policy experiment.

Before describing the counterfactual, it is worth considering whether reducing people’s overconfidence would be feasible at all. Psychologists have long been interested in whether a number of different behavioral biases including overconfidence can be reduced or eliminated (e.g. Fischhoff (1982), Sanna et al. (2002), Lau and Coiera (2009), and Fleisig (2011)), focusing primarily on laboratory settings. In Hoffman (2011b), I conducted a field experiment where workers at Firm B were informed about over-prediction of mileage by workers at Firm A. I show that the intervention substantially reduces overconfidence, though the effects fade over time. Alternatively, debiasing of overconfidence might occur if workers are shown information about the distribution of performance of other workers in the population or at a particular company. Debiaising could also involve individual-specific information, such as more detailed performance feedback or information on how past prediction compared with actual performance. Outside the psychology literature, legal scholars have also taken an interest in debiasing, e.g. Jolls and Sunstein (2006).\textsuperscript{78}

\textsuperscript{77}One could also interpret the counterfactual as a potential public policy of legally banning training contracts. In the context of the model, the ban would be interpreted as shutting down the career option of trucking for those who would only get trained if training contracts are feasible. Given that there are also private trucking schools and community colleges that drivers today receive training at, imposing a training contract ban would not mean that no one would receive training. Even if training contracts were to lower worker welfare, it is far from obvious that public policy should optimally restrict them. For example, it might be that the gain to firms from training contracts far exceeds the cost to workers. Given that I find a loss on average to workers from restricting training contracts, this leans strongly against a policy of restricting training contracts.

\textsuperscript{78}In addition to discussing information as a form of debiasing, Jolls and Sunstein (2006) also discuss how various legal arrangements may affect the impact of 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.
To examine how the effects of debiasing, I simulate the structural model with the overconfidence mass points reduced. Of course, the counterfactual is agnostic with respect to how the debiasing would occur. 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 be seen in Table 12. 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 significantly raises worker welfare since worker stay-or-quit decisions become less distorted from the 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. In addition, higher turnover means that the company is forced to pay training costs to repay more 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 12, 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.

### 9.4 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, they will additionally become less likely to be willing to sign up for the contract.

An optimal training contract is a penalty for quitting in every week 1, 2, ..., which is an infinite-dimensional problem. For several reasons (which I discuss below), I use computational methods instead of addressing the problem analytically. Even with modern computational tools, I need to simplify the problem. I assume first that the training contract cannot specify a penalty for longer than 110 weeks, the time period over which my workers are observed. Second, I focus on optimal
linear contracts within the first 110 weeks. This can be achieved by choosing an optimal penalty in week 1 and an optimal penalty in week 110.\textsuperscript{79}

I use the structural model to simulate trucker careers under different linear training contracts. Increasing penalties for quitting has five effects. First, using higher penalties increases retention, thereby increasing the time during which new workers bring in earnings. Second, using higher penalties will prevent some low productivity workers from quitting who otherwise would have quit. Third, using a higher quit penalty increases the amount of penalty receive for each quit. Fourth, the third effect is counteracted by the firm receiving fewer penalty payments due to fewer quits. Fifth, an increase in training contracts may have an effect on selection, changing both the number and characteristics of people who are willing to work for the company.

Column 1 of Table 13 reports the optimal contract in the baseline situation, before any debiasing has occurred. The optimal contract is decreasing from week 1 to week 110, but begins at a higher level than was used in the 18-month contract. The other columns repeat the simulations from 12, but allow firms to optimally adjust their training contracts. As can be seen, when overconfidence or learning or removed, the penalties for the optimal contract increase. This is because overconfidence and learning act as substitutes for more stringent penalties. Overconfidence about one’s productivity or the benefit of waiting to learn your true productivity are both reasons not to quit, as is having a stronger quit penalty. Thus, design of optimal training contracts rests on properly accounting for overconfidence and learning.\textsuperscript{80}

In the analysis of debiasing with no contractual response, debiasing is shown to increase worker welfare while decreasing firm profits. When firms are allowed to optimally adjust their contracts, the added gain to worker welfare is substantially smaller.

10 Conclusion

The question of how general training is provided despite the hold-up problem 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. These effects appear to be primarily driven by incentives instead of selection. To understand worker quit patterns, I develop a new approach for studying the relationship between learning, overconfidence, and quitting. A model with both learning and

\textsuperscript{79}The initial no contract regime was, of course, a linear contract, and the 18 month contract was close a linear contract. The 12-month contract was not a linear contract, as the penalty changed discontinuously at 52 weeks. I have also considered optimal step contracts, where contractual penalties are chosen to last for different periods of time.

\textsuperscript{80}Assuming that debiasing were to occur, an important question is at what point in time it would occur.
overconfidence provides a parsimonious fit for some of the data’s key features. Overconfidence decreases over time, but workers persist in their overconfidence, even after receiving numerous signals. On the whole, workers would be worse off if training contracts were banned, but very overconfident workers would be made better off. Alternatively, a policy of reducing worker overconfidence would increase worker welfare. However, such a policy might reduce firm profits so much that training would no longer be profitable.

To reach the above conclusions, a number of simplifying assumptions were made. I focused only on the quitting decision of the worker without modeling the firing decision of firms. Although firing is over five times less common than quitting in the data, future work may wish to consider the game played between workers and firms. I also focus on the decisions of one firm instead of considering the competition between different firms offering different training contracts.

When workers learn about their productivity and are overconfident, firms may wish to modify different features of their compensation system. In situations when firms can choose to pay flat wages or piece rates, paying a piece rate may be particularly appealing if workers are overconfident by making it easier for workers to satisfy their reservation utility. Future work should analyze the equilibrium interplay between worker behavior and firms’ contractual choices, both for training contracts and other types of contracts.
References


___, ___, ___, and ___, “Overconfidence is a Social Signaling Bias,” 2010. IZA Working paper.


40


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 >> 5,000. These figures plots 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: Impacts of Contracts of Quitting by Quarter of Tenure, OLS

Notes: This table reports the coefficients 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 3. 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 Effect of Training Contracts on Quitting Before and After the Contract Changes (with 95% CIs)

Notes: This figure plots the quit rates during specific tenure levels before and after the transition to the 12-month and 18-month contracts at different schools. 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. Controls include school fixed effects, year of hire fixed effects, and demographic controls, as in Equation 4.
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: Productivity and Believed Productivity, by Tenure and Across People

This figure analyzes actual and believed productivity for 699 drivers in the driver subset. The top two figures compare actual and predicted productivity with tenure. The top right figure is a local polynomial regression an Epanechnikov and an optimal bandwidth. The bottom two figures plot the distribution of overconfidence across people.
Figure 7: Are Workers Overconfident About their Outside Option? Comparison of Firm A Believed Outside Option Earnings with Earnings of Similar Workers in the CPS

Notes: This figure compares 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+. CPS uses income and earnings data 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 8: 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 is 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.
Figure 9: 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 is 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.
Figure 10: 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 is 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.
Figure 11: Mass Points from Full Model with Six Mass Points

Note: These figures plot the location of the 6 mass points estimated with a model with overconfidence and generalized learning. The mass points are proportional in size to their estimated frequency. As can be seen, the data suggest a strong negative relationship between overconfidence and taste for the job.
### Table 1: Summary Statistics

#### Panel A: All New Drivers at Firm A

<table>
<thead>
<tr>
<th>Variable</th>
<th>No Contract</th>
<th>12-Month Contract</th>
<th>18-month Contract</th>
</tr>
</thead>
<tbody>
<tr>
<td>African-American</td>
<td>0.19</td>
<td>0.19</td>
<td>0.19</td>
</tr>
<tr>
<td>Hispanic</td>
<td>0.07</td>
<td>0.04</td>
<td>0.03</td>
</tr>
<tr>
<td>Female</td>
<td>0.08</td>
<td>0.08</td>
<td>0.08</td>
</tr>
<tr>
<td>Married</td>
<td>0.35</td>
<td>0.35</td>
<td>0.38</td>
</tr>
<tr>
<td>Age</td>
<td>37.27</td>
<td>37.00</td>
<td>37.25</td>
</tr>
<tr>
<td>Online Application</td>
<td>0.47</td>
<td>0.55</td>
<td>0.70</td>
</tr>
<tr>
<td>Smoker</td>
<td>0.30</td>
<td>0.42</td>
<td>0.40</td>
</tr>
<tr>
<td>Drivers</td>
<td>0.09 N</td>
<td>0.73 N</td>
<td>0.18 N</td>
</tr>
</tbody>
</table>

#### Panel B: Drivers in Data Subset

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>African-American</td>
<td>895</td>
<td>0.11</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Hispanic</td>
<td>895</td>
<td>0.02</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Female</td>
<td>895</td>
<td>0.10</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Married</td>
<td>895</td>
<td>0.41</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Age</td>
<td>894</td>
<td>36.46</td>
<td>21.06</td>
<td>69.21</td>
</tr>
<tr>
<td>Exemptions</td>
<td>846</td>
<td>0.40</td>
<td>0</td>
<td>97</td>
</tr>
<tr>
<td>Number of Kids</td>
<td>895</td>
<td>0.96</td>
<td>0</td>
<td>7</td>
</tr>
<tr>
<td>Online Application</td>
<td>889</td>
<td>0.67</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Smoker</td>
<td>787</td>
<td>0.46</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Years of Schooling</td>
<td>895</td>
<td>12.85</td>
<td>9</td>
<td>18</td>
</tr>
<tr>
<td>High School Dropout</td>
<td>895</td>
<td>0.04</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>High School Graduate</td>
<td>895</td>
<td>0.40</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Some College</td>
<td>895</td>
<td>0.34</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Technical School</td>
<td>895</td>
<td>0.14</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>College Degree or More</td>
<td>895</td>
<td>0.08</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Credit Score</td>
<td>784</td>
<td>585.96</td>
<td>407</td>
<td>813</td>
</tr>
<tr>
<td>No Credit Score</td>
<td>895</td>
<td>0.12</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Notes: Restricted to new drivers with over 1,000 weekly miles on average. Married is compared to single and unspecified. Female is compared to male and unspecified. 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.
Table 2: Impact of the Training Contracts on Quitting – Cox Model, Diff-in-Diff

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>12m contract</td>
<td>-0.179***</td>
<td>-0.172***</td>
<td>-0.208***</td>
<td>-0.202***</td>
<td>-0.182***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.045)</td>
<td>(0.045)</td>
<td>(0.051)</td>
<td>(0.052)</td>
<td>(0.054)</td>
<td></td>
</tr>
<tr>
<td>18m contract</td>
<td>-0.110*</td>
<td>-0.120**</td>
<td>-0.115*</td>
<td>-0.126*</td>
<td>-0.107</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.060)</td>
<td>(0.060)</td>
<td>(0.068)</td>
<td>(0.068)</td>
<td>(0.069)</td>
<td></td>
</tr>
<tr>
<td>State unemployment rate</td>
<td>-0.055***</td>
<td>-0.049***</td>
<td>-0.062***</td>
<td>-0.049***</td>
<td>-0.054***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.012)</td>
<td>(0.013)</td>
<td>(0.014)</td>
<td>(0.014)</td>
<td></td>
</tr>
<tr>
<td>Avg miles to date × 100</td>
<td>-0.060***</td>
<td>-0.048***</td>
<td>-0.049***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12m contract * (wks≤52)</td>
<td></td>
<td></td>
<td></td>
<td>-0.367***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.066)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>12m contract * (52&lt;wks≤78)</td>
<td></td>
<td></td>
<td></td>
<td>0.058</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.082)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>12m contract * (wks&gt;78)</td>
<td></td>
<td></td>
<td></td>
<td>0.042</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.087)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>18m contract * (wks≤52)</td>
<td></td>
<td></td>
<td></td>
<td>-0.016</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.079)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>18m contract * (52&lt;wks≤78)</td>
<td></td>
<td></td>
<td></td>
<td>-0.900***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.118)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>18m contract * (wks&gt;78)</td>
<td></td>
<td></td>
<td></td>
<td>-0.104</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.131)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time FE (yr)</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Cohort FE (yr of hire)</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Training School FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Demographic Controls</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>M</td>
<td>M</td>
<td>0.89M</td>
<td>0.89M</td>
<td>0.79M</td>
<td>0.79M</td>
</tr>
</tbody>
</table>

Notes: An observation is a driver-week. The regressions are Cox proportional hazard models, with robust standard errors 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. Productivity is given in terms of hundreds of miles driven per week. The exact \( M \) is withheld to protect firm confidentiality, \( M >> 100,000 \). * significant at 10%; ** significant at 5%; *** significant at 1%
### Table 3: Impact of the Training Contracts on Firing – Cox Model, Diff-in-Diff

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>12m contract</td>
<td>-0.031</td>
<td>-0.030</td>
<td>-0.059</td>
<td>-0.057</td>
<td>-0.026</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.074)</td>
<td>(0.074)</td>
<td>(0.091)</td>
<td>(0.091)</td>
<td>(0.094)</td>
<td></td>
</tr>
<tr>
<td>18m contract</td>
<td>0.045</td>
<td>0.044</td>
<td>0.071</td>
<td>0.059</td>
<td>0.116</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.097)</td>
<td>(0.097)</td>
<td>(0.119)</td>
<td>(0.118)</td>
<td>(0.120)</td>
<td></td>
</tr>
<tr>
<td>State unemployment rate</td>
<td>-0.005</td>
<td>0.019</td>
<td>0.007</td>
<td>-0.014</td>
<td>-0.018</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.021)</td>
<td>(0.021)</td>
<td>(0.024)</td>
<td>(0.024)</td>
<td></td>
</tr>
<tr>
<td>Avg miles to date × 100</td>
<td>-0.072***</td>
<td>-0.067***</td>
<td>-0.067***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12m contract * (wks≤52)</td>
<td></td>
<td></td>
<td></td>
<td>-0.065</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.111)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>12m contract * (52&lt;wks≤78)</td>
<td>-0.103</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.179)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>12m contract * (wks&gt;78)</td>
<td></td>
<td></td>
<td></td>
<td>0.167</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.157)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>18m contract * (wks≤52)</td>
<td></td>
<td></td>
<td></td>
<td>0.169</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.136)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>18m contract * (52&lt;wks≤78)</td>
<td></td>
<td></td>
<td></td>
<td>-0.002</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.204)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>18m contract * (wks&gt;78)</td>
<td></td>
<td></td>
<td></td>
<td>0.016</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.212)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Time FE (yr)</th>
<th>Yes</th>
<th>Yes</th>
<th>Yes</th>
<th>Yes</th>
<th>Yes</th>
<th>Yes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cohort FE (yr of hire)</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Training School FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Demographic Controls</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>$M$</td>
<td>$M$</td>
<td>$0.89M$</td>
<td>$0.89M$</td>
<td>$0.79M$</td>
<td>$0.79M$</td>
</tr>
</tbody>
</table>

Notes: An observation is a driver-week. The regressions are Cox proportional hazard models, with robust standard errors 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. Productivity is given in terms of hundreds of miles driven per week. The exact $M$ is withheld to protect firm confidentiality, $M >> 100,000$. * significant at 10%; ** significant at 5%; *** significant at 1%
### Table 4: Selection Effects of Training Contracts

#### Panel A: Selection on Productivity

<table>
<thead>
<tr>
<th></th>
<th>All Weeks</th>
<th>Exclude 0 Mile Weeks</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>12m contract</td>
<td>-6.30</td>
<td>-3.29</td>
</tr>
<tr>
<td></td>
<td>(26.22)</td>
<td>(26.34)</td>
</tr>
<tr>
<td>18m contract</td>
<td>-37.70</td>
<td>-36.40</td>
</tr>
<tr>
<td></td>
<td>(28.83)</td>
<td>(28.80)</td>
</tr>
<tr>
<td>Controls</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>M 0.86M</td>
<td>0.85M 0.75M</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.24</td>
<td>0.21</td>
</tr>
</tbody>
</table>

#### Panel B: Selection on Other Characteristics

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dep Var:</td>
<td>Black</td>
<td>Hispanic</td>
<td>Female</td>
<td>Married</td>
<td>Age</td>
<td>Smoker</td>
<td>Online Ap</td>
</tr>
<tr>
<td>12m contract</td>
<td>-0.009</td>
<td>0.021**</td>
<td>0.012</td>
<td>-0.016</td>
<td>0.111</td>
<td>0.050*</td>
<td>0.055**</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.017)</td>
<td>(0.399)</td>
<td>(0.027)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>18m contract</td>
<td>0.006</td>
<td>0.014</td>
<td>0.023</td>
<td>-0.005</td>
<td>0.574</td>
<td>0.062*</td>
<td>0.047*</td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.013)</td>
<td>(0.015)</td>
<td>(0.024)</td>
<td>(0.541)</td>
<td>(0.033)</td>
<td>(0.028)</td>
</tr>
<tr>
<td>Observations</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>0.72N</td>
<td>0.70N</td>
<td>0.82N</td>
</tr>
</tbody>
</table>

Notes: Panel A reports OLS regressions of productivity (miles per week) on training contract dummies and controls. Standard errors clustered by driver in parentheses. In Panel A, an observation is a driver-week. Panel B reports OLS regressions of driver characteristics on training contract dummies and controls. Robust standard errors in parentheses. In Panel B, an observation is a driver. The exact $M$ (driver weeks) and $N$ (drivers) are withheld to protect firm confidentiality, $M >> 100,000$. * significant at 10%; ** significant at 5%; *** significant at 1%
Table 5: Do Productivity Beliefs Predict Quitting?

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

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: Do Productivity Beliefs Predict Productivity? OLS Regressions

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

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 7: Structural Model Estimates

<table>
<thead>
<tr>
<th></th>
<th>No Bias</th>
<th>Belief Bias</th>
<th>Belief Bias 2 Types</th>
</tr>
</thead>
<tbody>
<tr>
<td>$$\tau$$ Scale param of idiosyncratic shock</td>
<td>1618</td>
<td>2206</td>
<td>3726</td>
</tr>
<tr>
<td></td>
<td>(136)</td>
<td>(291)</td>
<td>(449)</td>
</tr>
<tr>
<td>Productivity Parameters</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$$\eta_0$$ Mean of prior productivity dist</td>
<td>2464</td>
<td>2025</td>
<td>2024</td>
</tr>
<tr>
<td></td>
<td>(9)</td>
<td>(17)</td>
<td>(18)</td>
</tr>
<tr>
<td>$$\sigma_0$$ Std dev of prior productivity dist</td>
<td>475</td>
<td>286</td>
<td>284</td>
</tr>
<tr>
<td></td>
<td>(16.5)</td>
<td>(10.1)</td>
<td>(9.9)</td>
</tr>
<tr>
<td>$$\sigma_y$$ Std dev of productivity shocks</td>
<td>707</td>
<td>706</td>
<td>706</td>
</tr>
<tr>
<td></td>
<td>(1.5)</td>
<td>(1.5)</td>
<td>(1.6)</td>
</tr>
<tr>
<td>Skill Gain Parameter</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$$s_0$$ Value of skills gained in wks 1-5</td>
<td>14.9</td>
<td>8.6</td>
<td>31.7</td>
</tr>
<tr>
<td></td>
<td>(3.5)</td>
<td>(5.9)</td>
<td>(9.0)</td>
</tr>
<tr>
<td>Taste UH Parameters</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$$\mu_1$$ Mass point 1 of taste UH</td>
<td>-248</td>
<td>-259</td>
<td>-736</td>
</tr>
<tr>
<td></td>
<td>(9.0)</td>
<td>(12.6)</td>
<td>(41.9)</td>
</tr>
<tr>
<td>$$\mu_2$$ Mass point 2 of taste UH</td>
<td>-106</td>
<td>-135</td>
<td>-150</td>
</tr>
<tr>
<td></td>
<td>(14.6)</td>
<td>(12.1)</td>
<td>(10.0)</td>
</tr>
<tr>
<td>$$\mu_3$$ Mass point 3 of taste UH</td>
<td>139</td>
<td>135</td>
<td>191</td>
</tr>
<tr>
<td></td>
<td>(39.3)</td>
<td>(33.3)</td>
<td>(63.1)</td>
</tr>
<tr>
<td>$$p_1$$ Probability of type 1, taste</td>
<td>0.55</td>
<td>0.34</td>
<td>0.12</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.06)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>$$p_2$$ Probability of type 2, taste</td>
<td>0.24</td>
<td>0.43</td>
<td>0.67</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.06)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>Belief Parameters</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$$\sigma_b$$ Std dev in beliefs</td>
<td>299</td>
<td>298</td>
<td>271</td>
</tr>
<tr>
<td></td>
<td>(0.3)</td>
<td>(0.3)</td>
<td>(0.3)</td>
</tr>
<tr>
<td>$$\tilde{\sigma}_y$$ Believed std dev of productivity shocks</td>
<td>3650</td>
<td>1888</td>
<td>2068</td>
</tr>
<tr>
<td></td>
<td>(134)</td>
<td>(82)</td>
<td>(81)</td>
</tr>
<tr>
<td>$$\eta_b$$ Belief bias</td>
<td>589</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(22)</td>
</tr>
<tr>
<td>$$\eta_{1,b}$$ Mass point 1 of belief UH</td>
<td>426</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(20)</td>
</tr>
<tr>
<td>$$\eta_{2,b}$$ Mass point 2 of belief UH</td>
<td>3649</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(41)</td>
</tr>
<tr>
<td>$$p_{1,b}$$ Probability of type 1, beliefs</td>
<td>0.94</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.16)</td>
</tr>
</tbody>
</table>

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 is from 699 drivers in the data subset, all of whom face the 12-month training contract.
Table 8: Structural Model, Newer Estimates

<table>
<thead>
<tr>
<th>Parameter</th>
<th>No Bias</th>
<th>Belief Bias</th>
<th>Belief Bias</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2 Types</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Scale param of idiosyncratic shock</strong></td>
<td>1891 (260)</td>
<td>1605 (180)</td>
<td>4207 (925)</td>
</tr>
<tr>
<td><strong>Mean of prior productivity dist</strong></td>
<td>2307 (28)</td>
<td>1595 (41)</td>
<td>1742 (33)</td>
</tr>
<tr>
<td><strong>Std dev of prior productivity dist</strong></td>
<td>521 (20.8)</td>
<td>275 (10.5)</td>
<td>276 (10.5)</td>
</tr>
<tr>
<td><strong>Std dev of productivity shocks</strong></td>
<td>706 (3.6)</td>
<td>706 (3.6)</td>
<td>705 (3.6)</td>
</tr>
<tr>
<td><strong>Mean of prior productivity dist</strong></td>
<td>251 (33)</td>
<td>485 (38)</td>
<td>343 (34)</td>
</tr>
<tr>
<td><strong>Skill gain level</strong></td>
<td>0.08 (0.01)</td>
<td>0.11 (0.02)</td>
<td>0.07 (0.01)</td>
</tr>
<tr>
<td><strong>Skill gain speed</strong></td>
<td>0.68 (0.30)</td>
<td>0.03 (0.01)</td>
<td>0.05 (0.01)</td>
</tr>
<tr>
<td><strong>Mass point 1 of taste UH</strong></td>
<td>-195 (56.7)</td>
<td>-345 (19.7)</td>
<td>-988 (211.6)</td>
</tr>
<tr>
<td><strong>Mass point 2 of taste UH</strong></td>
<td>-61 (58.1)</td>
<td>-81 (30.0)</td>
<td>27 (58.5)</td>
</tr>
<tr>
<td><strong>Mass point 3 of taste UH</strong></td>
<td>180 (73)</td>
<td>231 (55)</td>
<td>634 (170)</td>
</tr>
<tr>
<td><strong>Probability type 1</strong></td>
<td>0.55 (0.07)</td>
<td>0.60 (0.04)</td>
<td>0.42 (0.06)</td>
</tr>
<tr>
<td><strong>Probability of type 2</strong></td>
<td>0.25 (0.06)</td>
<td>0.19 (0.04)</td>
<td>0.35 (0.06)</td>
</tr>
<tr>
<td><strong>Std dev in beliefs</strong></td>
<td>298 (1.4)</td>
<td>297 (1.4)</td>
<td>271 (1.3)</td>
</tr>
<tr>
<td><strong>Believed std dev of productivity shocks</strong></td>
<td>3481 (167)</td>
<td>1295 (82)</td>
<td>1759 (108)</td>
</tr>
<tr>
<td><strong>Belief bias</strong></td>
<td>722 (31)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Mass Point 1 of belief UH</strong></td>
<td>466 (25)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Mass Point 2 of belief UH</strong></td>
<td>3899 (139)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Prob of Type 1</strong></td>
<td>0.93 (0.01)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Log-likelihood</strong></td>
<td>-91024</td>
<td>-90731</td>
<td>-89787</td>
</tr>
<tr>
<td><strong>Number of workers</strong></td>
<td>699</td>
<td>699</td>
<td>699</td>
</tr>
</tbody>
</table>

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 is from 699 drivers in the data subset, all of whom face the 12-month training contract.
Table 9: Robustness: Model Fit Under Different Assumptions

Panel A: Log-likelihood Under Different Mass Points and Belief Cutoffs

<table>
<thead>
<tr>
<th>Mass Points</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>High belief cutoff</td>
<td>-89878</td>
<td>-89283</td>
<td>-89033</td>
<td>-88954</td>
<td>-88918</td>
</tr>
<tr>
<td>Low belief cutoff</td>
<td>-87735</td>
<td>-87411</td>
<td>-87227</td>
<td>-87135</td>
<td>-87116</td>
</tr>
</tbody>
</table>

Panel B: Log-likelihood Under Different Discount Factors

<table>
<thead>
<tr>
<th>Annualized discount factor</th>
<th>0</th>
<th>0.8</th>
<th>0.9</th>
<th>0.95</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log-likelihood</td>
<td>-89322.9</td>
<td>-89282.6</td>
<td>-89283.1</td>
<td>-89283.3</td>
</tr>
<tr>
<td>Likelihood ratio statistic</td>
<td>80.65</td>
<td>1.02</td>
<td>1.48</td>
<td></td>
</tr>
<tr>
<td>p values for other delta vs. 0.8</td>
<td>0.00</td>
<td>0.24</td>
<td>0.16</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Panel A presents the log likelihood from estimation under different discount factors. The numbers in the table are annualized discount factors. For example, the annualized discount factor of 0.8 in the table corresponds to a weekly discount factor of 0.9957. The data strongly reject a myopic model. The fit is better with an annualized discount factor of 0.8, but I cannot that the fit is equally good with higher discount factors. Panel B presents the log likelihood from estimation using different belief cutoffs and different numbers of mass points. The high belief cutoff is 10,000 miles and the lower belief cutoff is 5,000 miles. The model involves three mass points and generalized learning. The data is from 699 drivers in the data subset, all of whom face the 12-month training contract.
**Table 10: Profits Under Different Contracts**

<table>
<thead>
<tr>
<th></th>
<th>No contract</th>
<th>12 month</th>
<th>18 month</th>
</tr>
</thead>
<tbody>
<tr>
<td>Profits per worker</td>
<td>-$1,306</td>
<td>$1,603</td>
<td>$1,867</td>
</tr>
<tr>
<td>Profits per truck</td>
<td>-$2,834</td>
<td>$1,810</td>
<td>$2,735</td>
</tr>
</tbody>
</table>

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.

**Table 11: Welfare Analysis of Restricting Workers from Signing Training Contracts**

<table>
<thead>
<tr>
<th></th>
<th>Overall</th>
<th>Low Overconf</th>
<th>High Overconf</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ex ante perceived utility from trying trucking:</td>
<td>$179,218</td>
<td>$171,700</td>
<td>$288,390</td>
</tr>
<tr>
<td>Actual utility from trying trucking:</td>
<td>$157,943</td>
<td>$159,020</td>
<td>$143,210</td>
</tr>
<tr>
<td>Outside option (receive under ban):</td>
<td>$149,462</td>
<td>$149,462</td>
<td>$149,462</td>
</tr>
<tr>
<td>Change in actual worker utility:</td>
<td>-$8,481</td>
<td>-$9,558</td>
<td>$6,252</td>
</tr>
<tr>
<td>Change in firm welfare:</td>
<td>-$1,603</td>
<td>-$1,603</td>
<td>-$1,603</td>
</tr>
</tbody>
</table>

Notes: This table presents information on the welfare consequences of banning training contracts. The top three rows present what workers perceive to be the value of being able to try out being a trucker, their actual average realized utility from doing so, and the lifetime value of their outside option. The perceived value exceeds the actual average value because workers are overconfident. Results are presented averaged over low and high overconfidence types, for low overconfidence types, and for high overconfidence types. High overconfidence types believe they will receive higher utility from trying trucking than low overconfidence types. In addition, they end up receiving lower welfare because overconfidence distorts their decisions. All values are given in dollars. 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.
### Table 12: Counterfactual Simulations, No Contractual Response

<table>
<thead>
<tr>
<th></th>
<th>Baseline</th>
<th>50% debias</th>
<th>100% debias</th>
<th>Reveal ability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Retention at 20 wks</td>
<td>0.74</td>
<td>0.62</td>
<td>0.48</td>
<td>0.45</td>
</tr>
<tr>
<td>Retention at 40 wks</td>
<td>0.54</td>
<td>0.43</td>
<td>0.32</td>
<td>0.31</td>
</tr>
<tr>
<td>Retention at 60 wks</td>
<td>0.42</td>
<td>0.34</td>
<td>0.26</td>
<td>0.26</td>
</tr>
<tr>
<td>Welfare per worker</td>
<td>$157,943</td>
<td>$159,415</td>
<td>$160,072</td>
<td>$160,535</td>
</tr>
<tr>
<td>Profits per worker</td>
<td>$1,603</td>
<td>-$42</td>
<td>-$7,685</td>
<td>$620</td>
</tr>
<tr>
<td>Profits per truck</td>
<td>$1,810</td>
<td>-$1,490</td>
<td>-$5,803</td>
<td>-$2,391</td>
</tr>
<tr>
<td>Ability at 20 wks</td>
<td>2,034</td>
<td>2,036</td>
<td>2,035</td>
<td>2,091</td>
</tr>
<tr>
<td>Ability at 40 wks</td>
<td>2,055</td>
<td>2,055</td>
<td>2,052</td>
<td>2,117</td>
</tr>
<tr>
<td>Ability at 60 wks</td>
<td>2,072</td>
<td>2,067</td>
<td>2,059</td>
<td>2,126</td>
</tr>
</tbody>
</table>

Notes: This table reports the results of the counterfactual simulations described in the text, while assuming that training contracts are not adjusted in response. Under the debiasing counterfactual, the overconfidence mass points $\eta_{b1}$ and $\eta_{b2}$ are reduced by 50% or 100%. Under the reveal ability counterfactual, the worker's ability is revealed to the worker after training. These calculations are made 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.
### Table 13: Counterfactual Simulations Allowing for Optimal Contractual Responses

<table>
<thead>
<tr>
<th>Optimal Penalty</th>
<th>Baseline</th>
<th>50% debias</th>
<th>100% debias</th>
<th>Reveal ability</th>
</tr>
</thead>
<tbody>
<tr>
<td>In week 1</td>
<td>$22,500</td>
<td>$15,000</td>
<td>$0</td>
<td>$30,000</td>
</tr>
<tr>
<td>In week 110</td>
<td>$7,500</td>
<td>$0</td>
<td>$0</td>
<td>$7,500</td>
</tr>
<tr>
<td>Welfare per worker</td>
<td>$147,469</td>
<td>$152,863</td>
<td>$162,656</td>
<td>$147,597</td>
</tr>
<tr>
<td>Retention at 20 wks</td>
<td>0.88</td>
<td>0.80</td>
<td>0.43</td>
<td>0.81</td>
</tr>
<tr>
<td>Retention at 40 wks</td>
<td>0.81</td>
<td>0.64</td>
<td>0.26</td>
<td>0.74</td>
</tr>
<tr>
<td>Retention at 60 wks</td>
<td>0.75</td>
<td>0.53</td>
<td>0.21</td>
<td>0.69</td>
</tr>
<tr>
<td>Profits per worker</td>
<td>$4,849</td>
<td>$910</td>
<td>-$5,097</td>
<td>$6,162</td>
</tr>
<tr>
<td>Profits per truck</td>
<td>$9,679</td>
<td>$7,013</td>
<td>-$11,405</td>
<td>$13,016</td>
</tr>
<tr>
<td>Ability at 20 wks</td>
<td>2,023</td>
<td>2,028</td>
<td>2,034</td>
<td>2,049</td>
</tr>
<tr>
<td>Ability at 40 wks</td>
<td>2,035</td>
<td>2,050</td>
<td>2,049</td>
<td>2,069</td>
</tr>
<tr>
<td>Ability at 60 wks</td>
<td>2,051</td>
<td>2,073</td>
<td>2,048</td>
<td>2,086</td>
</tr>
</tbody>
</table>

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 debiasing counterfactual, the overconfidence mass points $\eta_{b1}$ and $\eta_{b2}$ are reduced by 50% or 100%. Under the reveal ability counterfactual, the worker’s ability is revealed to the worker after training. These calculations are made 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.
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 similar to that in Peterson (2010). Since my paper is interested in the optimal design of training contracts, 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 \( \eta \). Workers have some non-pecuniary taste for the job \( \varepsilon \), which they learn after training. I assume that \( \varepsilon \) 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 \( \varepsilon \) is realized, the worker decides whether to quit, and payoffs are realized.

The firm’s problem can be written as:

\[
\max_{w,k} \left( 1 - F(-w\eta - k + \bar{W}) \right) \ast (\eta - w\eta) + F(-w\eta - k + \bar{W})\theta k - c
\]

\[
r \leq E \max (w\eta + \varepsilon, \bar{W} - k)
\]

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

\[
f (-W - k + \bar{W}) (\eta - W - \theta k) - (1 - F (-W - k + \bar{W})) + \lambda \frac{\partial E_{\text{max}}}{\partial W} = 0
\]

\[
f (-W - k + \bar{W}) (\eta - W - \theta k) + \theta F (-W - k + \bar{W}) + \lambda \frac{\partial E_{\text{max}}}{\partial k} = 0
\]

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 \( \theta > 0 \).\(^{81}\) Because it is not possible to satisfy the IR constraint while setting \( k = 0 \) (since \( \bar{W} \geq r \) and \( \varepsilon \) has full support over the real line), \( k = 0 \) cannot be optimal.\(^{82}\)

\(^{81}\)The 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.

\(^{82}\)Setting \( W \) 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.
To analyze retention, let $P$ denote the retention probability. Note then that $W = (W - k - \Psi^{-1}(P))$. Profits are then given by:

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

(14)

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

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

(15)

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

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

(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 $k = 0$).  

**Example 2** Consider where $\epsilon = \epsilon_1 - \epsilon_2$ where $\epsilon_1$ and $\epsilon_2$ are zero-mean type I extreme value random variables. Assume also that $\theta = 0$. The firm will choose $w$ and $k$ to maximize

$$\max_{w,k}(1 - F(-w\eta - k + \overline{W})) \ast (1 - w)$$

$$r = E \max_{w,k} (w\eta + \epsilon, W - k)$$

In this case, the firm’s problem can be written out as

$$\max_{w} \Lambda (w\eta + k - \overline{W})(1 - w)$$

$$\exp(r) = \exp(w\eta) + \exp(\overline{W} - k)$$

where $\Lambda(x) = \frac{\exp(x)}{1 + \exp(x)}$. Solving the IR constraint yields that $w\eta = \log \left( \exp(r) - \exp(\overline{W} - k) \right)$. It will be convenient to use the notation of $W = w\eta$ and $Z = W + k - \overline{W}$. One can then differentiate the profit function with respect to $k$: $\pi_k = \Lambda'(Z) \ast (W' + 1) \ast (\eta - W) - \Lambda(Z) \ast W'$. It can be shown that $\pi_k$ is positive everywhere except at $k = \infty$ where $\pi_k = 0$, since $\pi_k = \exp(r) \ast (\eta - W - 1) \ast \frac{\exp(Z)}{1 + \exp(Z)} \ast \frac{1}{\exp(r) - \exp(\overline{W} - k)}$. Thus, the firm will choose $k = \infty$, or if there is a limit on the legally permissible $k$, it will choose $k$ as high as possible. When $k = \infty$, all workers are retained, so retention was increased from the scenario absent a training contract.

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

$$\arg \max_{w,k}(1 - F(-w\eta' - k + \overline{W})) \ast (1 - w)\eta + F(-w\eta' - k + \overline{W})\theta k - c$$

$$E \max(w\eta' + \epsilon, W - k) \geq r$$

where $\eta'$ is the worker’s belief about her productivity.

---

83I am grateful to Ben Hermalin for the proof that retention increases.

84Indeed, 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.
Proposition 3 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 her current earnings to be more responsive to her current productivity than her outside option. Formally, suppose that \( w > \frac{dW}{d\eta} \), where \( w \) solves \( \eta - w\eta = G(-w\eta + W) \); then an increase in \( \eta' \) increases profits so long as

\[
\frac{\partial}{\partial \eta} \left( \frac{w - \eta}{\eta} \right) > 0.
\]

Proof. Note that the outside option \( W \) may depend on \( \eta' \). 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 \( E_{\max}(w\eta' + \epsilon, W) > E_{\max}(w\eta + \epsilon, W) \)). Further, given the rational wage \( w^* \), an increase in productivity beliefs increases profits so long as \( \text{sgn} \left( \frac{d(1 - F(-w\eta' - k + W))}{d\eta} \right) = \text{sgn} \left( -f' \left( -w + \frac{dW}{d\eta} \right) \right) = \text{sgn} \left( \frac{w - \frac{dW}{d\eta}}{\frac{dW}{d\eta}} \right) = +. \) 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 \( \eta \) to \( \eta' \) increases profits under \( (w^*, k^*) \) so long as \( w > \frac{dW}{d\eta^*} \) 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.

Example 4 Consider the example where \( \epsilon = \epsilon_1 - \epsilon_2 \) where \( \epsilon_1 \) and \( \epsilon_2 \) are type I extreme value random variables and where \( W = r \). When workers have rational beliefs, the profit maximizing solution is to have \( k = \infty \) and \( w = \frac{r}{\eta_1} \), and profits are \( \eta - \eta_2 - \frac{r}{\eta_1} = \eta - r - r \). When workers have biased beliefs, the problem becomes:

\[
\max_{w,k} \Lambda(w\eta' + k - r)(1 - u) = \exp(r) = \exp(w \eta') + \exp(r - k).
\]

The profit maximizing solution is \( k = \infty \) and \( w = \frac{r}{\eta} \), and profits are \( \eta - \frac{r}{\eta} - \frac{r}{\eta} < 0 < \eta - r - c \). Then firms will not train when workers have rational beliefs, even when they have any choice of training contract, whereas they will train when workers are overconfident.

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 5 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.

B Structural Model Derivations

One of the key equation in the model is the expected maximum or \( E_{\max} \) term. I have that:

\[\text{Similar derivations can be found in Rust (1987) and Stange (forthcoming)}\]
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 $V^Q$ is independent of the state variable. The fourth equality integrates out $y_t$, which are not observed when the driver makes her 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 $Pr(y^k_t|y_1,\ldots, y_{t-1})$ 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:

$$L_i = \int L(d_{i1}, \ldots, d_{it}, y_{i1}, \ldots, y_{it}, b_{i1}, \ldots, b_{it}|\alpha, \eta_i) f(\alpha, \eta_i) \, d\alpha d\eta_i$$

$$= \left\{ \int \{ L(d_{i1}, \ldots, d_{it}|y_{i1}, \ldots, y_{it}, b_{i1}, \ldots, b_{it}, \alpha, \eta_i) \ast L(b_{i1}, \ldots, b_{it}|y_{i1}, \ldots, y_{it}, \alpha, \eta_i) \} \, d\alpha d\eta_i \right\} \int_{y_{i1}}^{y_{it}} \{ L(d_{i1}, \ldots, d_{it}|y_{i1}, \ldots, y_{it}, \alpha, \eta_i) \ast L(b_{i1}, \ldots, b_{it}|y_{i1}, \ldots, y_{it}, \alpha, \eta_i) \} \, d\alpha d\eta_i$$

$$= \left\{ \int \prod_{s=1}^{t} L(d_{is}|d_{i1}, \ldots, d_{i(s-1)}, y_{i1}, \ldots, y_{it}, \alpha, \eta_i) \ast \prod_{s=1}^{t} L(b_{is}|b_{i1}, \ldots, b_{i(s-1)}, y_{i1}, \ldots, y_{it}, \alpha, \eta_i) \, d\alpha d\eta_i \right\} \int_{y_{i1}}^{y_{it}} \prod_{s=1}^{t} L(d_{is}|y_{i1}, \ldots, y_{i(s-1)}, \alpha, \eta_i) \, d\alpha d\eta_i$$

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

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

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

and where $\gamma_s = \frac{s \sigma_y^2}{s \sigma_y^2 + \sigma_y^2}$ and $\Omega_s = \frac{s \sigma_y^2}{s \sigma_y^2 + \sigma_y^2} + \sigma_y^2$.\textsuperscript{86}

\textsuperscript{86}This follows by applying the standard formula for the conditional density for a multivariate normal distribution: $X_1 | (X_2 = x_2) \sim N(\mu_1 + \Sigma_{12} \Sigma_{22}^{-1} (x_2 - \mu_2), \Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21})$.