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Abstract

One of the most vexing public policy issues is the extent to which governments should intervene into private contractual relationships. The purpose of this paper is to explore both theoretically and empirically the extent to which such interventions may enhance efficiency. In the case of employment law, economists have traditionally taken the view that intervention, such as protection against wrongful discharge, simply undoes the original intent of the parties to the agreement. We find that both the good faith and the implied contract exceptions to employment at will may enhance employment in occupations characterized by high levels of investment. These results suggest that under the appropriate conditions courts may enhance the operation of a competitive market by setting appropriate default remedies for breach of contract.

JEL Classification: J11, J21, J31, J61, K12, K31

1 Introduction

One of the most vexing public policy issues is the extent to which governments should intervene into private contractual relationships. The purpose of this paper is to explore both theoretically and empirically the extent to which such interventions may enhance efficiency. In the case of employment law, economists have traditionally taken the view that intervention, such as protection against wrongful discharge, simply undoes the original intent of the parties to the agreement. Therefore, such interventions cannot enhance welfare and are more likely to reduce social welfare.

In practice, the contracts that govern complex relations such as employment are incomplete. Therefore, when an unanticipated event occurs, parties may ask the courts to provide the missing terms. In the United States, the traditional common law rule is employment at-will: each party is free to leave at any point without being required to provide a reason and without facing any liability. Under this rule, disputes requiring intervention should be rare because differences in opinion simply result in a dissolution of the relationship.

This does not imply that the at-will rule is always an *efficient* contract.[1] As Williamson, Wachter, and Harris (1975) illustrate, employers and employees make significant relationship specific investments that may require some contractual protection. In a competitive market, one expects parties to discover and to use such efficient contracts, and hence there is a general presumption that, whenever the parties do not specify an exception to at-will employment, the at-will rule is the presumptive choice of the parties.

In the context of the efficient labor employment debate, there is also a general presumption among economists that at-will employment allows firms to efficiently adjust their labor force in response to demand shock and to shed the least productive workers. In a sense, at-will employment protects firms from poor workers (see in particular the 1994 OECD jobs study that calls for a general reduction in employment protection). If employment at-will is regarded as an optimal strategy, then how do we explain the general erosion of the common law rule of employment at-will that has been observed in the United States?[2]

Even a cursory reading of some employment cases reveals a rich tapestry of poor, incompetent and in some cases dishonest behavior by employers.[3] In response, the courts have provided employees in these cases some relief from the behavior of their employers. For example, the good faith exception to employment at-will evolved in response to employers who attempted to dismiss an employee in order to avoid paying a commission upon a sale negotiated by the employee.[4] In these cases, the courts can be seen as improving the quality of the contract between the employer and employee.

Hence, from the micro perspective of a specific case coming before the courts, it would appear that the courts are not making unreasonable demands upon employers, they are simply requiring employers to behave in a fair and just manner. These rulings, as much of the literature emphasizes, place additional burdens upon employers who already manage their employees well.

This leads to two questions. First, does requiring poor employers to be more diligent in monitoring their workers increase efficiency? Second, if this is the case, can the introduction of wrongful discharge laws enhance efficiency *on average* - since it applies to both good and bad employers?

In this paper, we make some progress on both questions. First, using the model of MacLeod (2003), we show that in theory requiring employers to provide a reason for dismissing employees can

[1] See MacLeod (2005) for a review of the literature and for a discussion of the conditions under which the at-will rule is not efficient.

[2] See Epstein (1984) critique of the erosion of at-will employment in the U.S.

[3] See Rothstein and Liebman (2003) for a review of the law; in particular chapter 10 discusses a number of discharge cases.

[4] See Wakefield v. Northern Telecom, 769 F.2d 109 (2d Cir.) 1985.

increase both the wages of employees *and* their productivity. The idea is straightforward. All jobs require some element of subjective evaluation of employees, and hence there is always a chance that the evaluation of the employer is erroneous. This can lead to lower wages and productivity by workers, but it can be corrected when employers are required to put into place systems of employee evaluation that produce verifiable information that is usable in court.

From previous research (discussed in more detail in the next section), there is substantial evidence that on average wrongful discharge laws may be detrimental to employment. As Heckman and Pagés (2004) observe in their introduction, this effect is largest in jobs with high turnover and fewer relationship specific investments because for these jobs the rules provide greater constraints on the efficient adjustment of labor. In jobs with lower turnover and higher human capital investments, such laws are more likely to constrain poor managers who do not properly monitor and document worker performance.

Accordingly, in our empirical work, we divide jobs according to different measures of human capital investment, and we find that the negative effect on employment is strongest in jobs with lower levels of investment - a result consistent with earlier findings. We also find - particularly in the case of the good faith exception to employment at-will - some evidence that wrongful discharge laws can have positive effects upon employment, with no corresponding decrease in wages. Hence, we may conclude that legal default rules introduced in response to observed wrongs may in some cases increase workers' welfare.

The agenda of the paper is as follows. In the next section, we discuss the specific exceptions to the common law rule of employment at-will that have been introduced in the United States in the past 20 years, and we review the prior literature that assesses empirically the impact of this legislation. Section 3 outlines a model that illustrates one mechanism by which employment law may enhance efficiency. This is followed by a description of the data, empirical methodology and empirical results. The paper concludes with a discussion of the results and directions for future research.

2 The Economics of Employment Law: Previous Literature

The previous economics literature on employment law addresses two issues. The first is whether the law has an impact at all. The second is whether a specific law has a negative or positive impact upon particular groups.

Edward Lazear (1990) observes that in a Coasian world the law acts as a constraint on the observed contract; however, parties can find ways to contract around the explicit rules. Even if this is difficult, firms would offer lower starting wages to pay for the cost of dismissing a worker later, and hence total employment would not be affected. Bentolila and Bertola (1990) provide one of the seminal models of employment protection law. They show that the theoretical impact of the law upon short run employment is ambiguous; however, if contracts are complete, then as Lazear (1990)'s argues, there would be no long run effect.[5]

Schwab (1993) provides an economic analysis of employment law, and he argues much of the case law is developed late in an employee's life-cycle. At that point there is a significant level of relationship specific capital, and hence they need more protection from opportunistic employers. In general, Schwab argues that employment law rationally provides rulings intended to enhance the employment relationship. In contrast, the 1994 OECD jobs study called for a general reduction in employment protection rules, in order to enhance flexibility in the labor market. Much of the subsequent empirical literature has focused upon measuring the costs arising from employment protection laws.

[5] See Bertola (2004) for an extention of this work to risk averse workers. In that case EPL (Employment Protection Legislation) plays a role in reallocating the cost of turnover from workers to firms, which in some cases increases efficiency. See also the recent work of Blanchard and Tirole (2004) where worker risk aversion plays a crucial role.

Consistent with Lazear (1990), Oyer and Schaefer (2000) show that employers can find ways to circumvent the Civil Rights Acts that protect workers based upon race or gender. They do this by moving from individual dismissal to mass layoffs during downturns. However, Chay (1998) does find some evidence that this act did improve the economic welfare of African Americans. Recent work by DeLeire (2000), Acemoglu and Angrist (2001), and Jolls and Prescott (2004) shows that the Americans with Disabilities Act harmed these individuals.

Apart from the Federal Acts, each state has adopted three classes of exceptions to employment at-will (Wrongful Discharge Laws or WDLs in short) during the 1970s and 1980s. These exceptions declare situations where the default employment relationship is not at-will. Each of them will be discussed in detail below.

2.1 Exceptions to Employment At-Will

Implied Contract Exception When a worker can verify that a permanent employment relationship is promised by his employer, then such employment can no longer be regarded as at-will and can be terminated only under just cause.[6] If a personnel manual given to employees specifies that termination is only with cause, then several court decisions view this as a binding contract. As Judge C. J. Wilentz states in the case of *Woolley v. Hoffmann-La Roch*: "it would be unfair to allow an employer to distribute a policy manual that makes the workforce believe that certain promises have been made and then to allow the employer to renege on these promises."

Such a rule simply requires the employer not to mislead the employee, and hence in principal it should be efficiency enhancing. Notice that if this were the only grounds for litigation, then evidence of a negative effect of the doctrine would imply that employers either knowingly deceived employees or erred in writing their employee handbooks. However, employee handbooks are not the only example of an implied contract. The case of *Pugh v. See's Candies* established the principle that a long employment with regular promotion establishes a long term contract.[7] Thus, the employer can only dismiss an employee with cause in these cases. Interestingly, the reason for Pugh's dismissal appeared to be capricious - Pugh simply disagreed with the firm's agreement with its union regarding employment policy and reported to his company that his current supervisor was a convicted embezzler. The supervisor subsequently fired Pugh. It was ruled at court that this fact was not sufficient for a case but that the length of good service was sufficient to establish an implied contract, and hence the court ruled that Pugh was wrongly dismissed.

This example illustrates a concrete case in which an employee is dismissed not because of an objective failing (otherwise one could provide cause) but because essentially he did not fit in with the new supervisor. If the contract were at-will, then dismissal would be immediate. Therefore, what this rule does is place a bar on dismissing long term employees who may not fit in, or if delinquent in their performance, the employers are unable to provide sufficient evidence of this poor performance.

Together, these rules impose a cost upon firms when they wish to dismiss an employee without cause. It is difficult to say what is the likely consequence of this law. Theoretically, if all agents are rational, then there should be no effect. However, if the rule reduces the effect of deception by employers, then we might get a positive effect. When relationship specific investments are larger, there is less turnover, and hence the negative effect of restricting dismissal is likely to be smaller. In this case, we expect the effect of the law to be less negative and possibly positive.[8]

The time pattern of the adoption of the implied contract exception to at-will-employment is

[6] Toussaint v. Blue Cross & Blue Shield 292 N,W.2nd. 880 (Michigan 1980) and Woolley v. Hoffmann-La Roch, Inc., 499 A.2d 515 (N.J. 1985).

[7] Pugh v. See's Candies, 171 Cal. Rptr 917 (Cal. Ct. App. 1981).

[8] See Farber (1999) for a review of the literature on wage profiles and the returns to specific investments.

illustrated in Figure 1. See also Figure 2 detailing the geographical extent of the changes. We have also plotted the evolution of the other two exceptions namely the good faith and the public policy exceptions which will be discussed below. It is not completely clear what motivated these changes. Krueger (1991) presents evidence that these law changes were in response to the uncertainty of the courts in applying the common law exceptions to employment at-will. If this is true, then these law changes did not actually change the law per se, but they reduced the uncertainty associated with its application. If this is the case, then the changes should lower legal costs, and hence if anything, the effects should be positive. This is at odds with the negative consequence of the law changes documented by Autor, Donohue, and Schwab (2006).

Good Faith Exception The implied contract rule requires the firm to provide cause when dismissing employees who are deemed to be on a long term contract. The good faith exception to employment at-will requires in addition that employees dismiss workers in a fair manner - they may not be required to provide a reason, but they cannot dismiss workers in a patently unjust manner. Under this exception, workers do not need to have the implicit promise of long term employment in order not to be dismissed unfairly. The rule is illustrated in the case of *Mitford v. Lasala*.[9] In this case, Mitford was an accountant fired from employment in which there was a profit sharing agreement. It was ruled that termination arose to ensure that Mitford would not share in profits to be realized. The courts ruled that "good faith and fair dealing... would prohibit firing [an employee] for the purpose of preventing him from sharing in future profits."

Currently, courts typically find a rather narrow application of this rule to the timing of dismissal and payment of compensation, rather than to other forms of bad behavior by employers. Typical examples of wrongful terminations that fit under this class are: i) a salesman being fired right before his commissions should be paid to him, or ii) an employee being dismissed in order to avoid paying retirement benefits.

As we can see from Figure 1 and 2, there are many fewer states adopting this law than in the case of the implied contract rule. Given the more narrow applicability of the rule, this may simply reflect the fact that courts in these states have adhered more closely to the common law principle of at-will employment, and hence there was a need for statutory intervention to deal with cases where employers avoid paying compensation by a presumptive dismissal. If so, then we might expect this rule to have a large impact.

This is not because of the effect upon firing costs, but because it corrects poorly drafted contracts. In the case of *Mitford v. Lasala*, the contract was quite clear, and it implied that the firm had no obligation to pay the bonus. Most employees would expect to be paid in such a case, but at the time of writing the agreement they simply would not expect the deception to occur. In such cases, the courts can enhance productive efficiency by essentially completing an incomplete contract.[10]

Public Policy Exception We also present results on the impact of the public policy exception to employment at-will. Under this exception, a termination is wrongful if it is a response to an employee's conduct that is not favored by the employer but is protected by law. The public policy exception covers the cases where an employee should not be dismissed if he refuses to violate a state's well-established public policy. Miles (2000) summarizes the four circumstances of terminations that fit under this class of exception.[11] These are (1) "an employee's refusal to commit an illegal act, such as perjury or price-fixing"; (2) "an employee's missing work to perform a legal duty, such as jury duty or military service"; (3) "an employee's exercise of a legal right, such as filing a workman's compensation claim"; and (4) "an employee's 'blowing the whistle,' or disclosing wrongdoing by the employer or fellow employees."

[9] Mitford v. Lasala, 666 P.sd 1000 (Alaska 1963).
[10] See Kornhauser and MacLeod (2005) for a further discussion of these issues.
[11] Page 78.

An example of this exception is the 1985 case of *Tameny v. Atlantic Richfield Co.*[12] Tameny, the dismissed employee, challenged the company's decision in court claiming that the discharge was due to the fact that he refused to perform the price-fixing scheme (which was unlawful) in favor of the company. Atlantic Richfield argued that since there was no employment contract, Tameny's employment was at-will and could be terminated at any time. California Supreme Court ruled in favor of Tameny, stating that an employer should not discharge an employee who obeyed the law and refused to perform an illegal act.

This exception does not, by itself, address the efficiency per se of the employment relationship, but rather it merely constrains the behavior of the firm according to other existing laws. In other words, the public policy exception helps to oversee that firms behave according to existing state's and federal laws. Therefore, we would not expect to see the public policy exception to have any effect upon employment and wages.

2.2 Employment Consequences of Exceptions to Employment At-Will

With increasing cost of discharge, firms will have the incentive to screen workers more carefully. Kugler and Saint-Paul (2004) find that the laws make it harder for unemployed workers to get a new job relative to currently employed workers because employers tend to think that the currently employed workers are less likely to be "lemons". One way for employers to avoid this cost of discharge is through the use of temporary help agencies that allow employers to refrain from the liability associated with long term employment. Autor (2003) shows that temporary help service employment has largely increased in association with the adoption of the implied contract exception. Schanzenbach (2003) finds that in association with the laws, full-time workers tend to have longer tenure. He, however, finds limited evidence of the laws' help increasing the return to tenure.

The empirical evidence on the effect of this rule on overall employment is mixed. An early work by Dertouzos and Karoly (1992) finds large negative effects of the exceptions to employment at-will. More recent work by Miles (2000) and Autor, Donohue, and Schwab (2006) finds much smaller effects. In fact, Miles (2000) finds no significant effects; although Autor, Donohue, and Schwab (2006) do get consistently negative effects, particularly for workers with marginal attachment to the workforce. They find that the negative effect of the law on employment is significantly smaller than estimated by Dertouzos and Karoly (1992) - about 0.6% to 0.8% on state's employment per population compared to Dertouzos and Karoly's estimate of 3%. Autor, Donohue, and Schwab (2004) explain that the differences between their results and those of Dertouzos and Karoly (1992) are due to the problematic instruments used by Dertouzos and Karoly (1992). They also argue that their results differ from those of Miles (2000) because they use a different classification of case laws in identifying the adoption dates. They argue that, with their classification, they "attempt to locate the first case in a state that might trigger a client letter from attorneys warning about a change in law" and therefore "maximize the chance of detecting economic effects of changes to the common law." [13] In this paper, we use the adoption dates classification developed by Autor, Donohue, and Schwab (2006) who kindly provided us with the data. This information is shown in Table 1.

In a recent study, Autor, Kerr, and Kugler (2005) use a data set that links workers to firms to assess the productivity implication of WDLs. They find that overall these law changes reduced labor flows and increased labor productivity, but they had little effect on total factor productivity. These results are consistent with the results we obtain in this paper.

The consequences of labor protection have also been extensively studied for developing countries, developed countries, and worldwide. The type of regulation and the intensity of the protection vary

[12] Tameny v. Atlantic Richfield Co., 27 Cal.3rd 167 (California 1980).
[13] Autor, Donohue, and Schwab (2004) page 7.

everywhere, even among the group of developed countries. The U.S.'s zero employment protection and the Europeans' excessive labor regulation are often compared. In most empirical studies, it seems like labor protection does more harm than good, even though some theories have predicted otherwise. In an empirical cross-country study, Botero, Djankov, La Porta, Lopez-de Silanes, and Shleifer (2004) show that employment protection has a negative effect on labor market outcome in terms of lower labor force participation and higher unemployment.

Finally, the book edited by Heckman and Pagés (2004) provides a comprehensive study of the impact of WDLs in Latin America. They find that on average, an increase in employment protection tends to be economically costly. However, they do find that an increase in employment protection is advantageous to incumbent workers, while lowering employment opportunities for new workers entering the labor market.

3 A Model of Wrongful Discharge Law

In this section, we introduce a simple model that illustrates the two channels through which wrongful discharge law affects employment and employee productivity. The model builds upon the results of MacLeod (2003) who extends the standard principal agent model to the case of subjective evaluation. He shows how the quality of the employment contract is affected by the quality of an employer's evaluation of employee performance. Building upon the idea that there can be variation in the quality of an employer's system of evaluation, we model the introduction of wrongful discharge as an increase in both the cost of firing a worker and in the quality of the evaluation of employee performance. The later occurs because WDLs create an incentive for the employer to reduce legal liability by collecting more accurate and verifiable information regarding employee performance. As MacLeod (2003) shows, if employer and employee use this common and more accurate signal, it leads to higher wages and performance.

We explore how both the level of and variations in productivity interact with changes in WDLs. To keeps matters as simple as possible, suppose we follow Jovanovic (1979) and suppose that all workers are identical and have an alternative wage of $w^0 > 0$. Variations in productivity arise from variations in match quality and from firm specific demand shocks that may lead to dismissal for reasons unrelated to worker behavior. In practice, workers vary in their ability; however, given that there is likely to be associative matching of workers to firms, this extension does not significantly alter the insights of the simple model.

Consider a two period model in which the firm decides to hire a worker in the first period. We extend this simple model in the next section to allow for training in the first period. This hiring decision is based upon the firm's initial estimate of match productivity, θ^0, normalized to lie in $[0,1]$. Production occurs in period 2. The realized productivity of the match is θ, and it is assumed to be $\theta = \theta^0$ with probability $\pi \in [0,1]$, and, with probability $1-\pi$, given by a draw from the distribution $g(\cdot)$ with values taken from $[0,1]$. The total number of firms is N. An increase in π corresponds to a decrease in variability of firm productivity and hence to a decrease in the probability that the firm will lay a worker off in period 2. The characteristics of a firm are summarized by the vector $\omega = \left\{\theta^0, \pi\right\}$.

The experiment we consider supposes that π is fixed, and for simplicity we assume that the initial distribution of θ^0 is the same as $g(\cdot)$ above. Thus, the *ex ante* and *ex post* distributions of productivity are fixed. Given that there is an unlimited supply of workers at the reservation wage w^0, the market equilibrium will be characterized by two cutoff productivities. In period 1 the cutoff productivity level is θ^A, so that firms with $\theta^0 \geq \theta^A$ hire a worker. *Ex post,* the cutoff productivity is θ^P, and hence workers with realized productivity $\theta < \theta^P$ are dismissed. Given that firing a worker is costly, it will be the case that $\theta^P \leq \theta^A$. We then explore the effect that labor market regulation has on these cutoff productivities. If θ^A falls as a function of regulation, then the regulation enhances employment, while if it rises, then regulation has a negative effect on employment.

As we discuss above, employment protection regulation has two effects. First, it creates a firing cost F that the firm must pay to a third party in the event of worker separation in period 2. As Lazear (1990) has shown, if regulation merely mandates a transfer to workers in the event of separation, then the employment contract can always undo the effects of a separation cost. In that case, regulation would have no effect on employment, but it might reduce starting wages. In order for firing costs to affect outcome, they must be a pure social loss to the relationship via payments to the courts, to lawyers and to additional administrative support staff created by the regulation.

To avoid the complications that arise from computing an inter-temporal value function (as in Jovanovic (1979)), we suppose that firms must make the decision to employ a worker in period 1, and then they must pay the firing cost F if the worker is dismissed in period 2. As is standard in the matching literature, dismissal occurs in period 2 if and only if current productivity is lower than the worker's outside option less the firing cost. Hence, an increase in legal costs leads to a lower θ^P in period 2.

The second effect of employment protection regulation is an increase in the quality of worker supervision. Employment protection regulation does not make firing a worker impossible; rather, it requires the firm to provide a valid reason for the dismissal. If the firm has systematic records of employee performance and can prove that the employee performed at an unacceptable level, then dismissal is justified. However, if such records are lacking, then the firm may be required to pay damages for an unjust dismissal. As a consequence, we should expect the lawyers in firms advising management to keep more careful and systematic records of employee performance.

We formally illustrate this effect using the model developed in section III of MacLeod (2003). There, employee effort, $\lambda \in [0, 1]$, is interpreted as the probability of effort resulting in a good outcome. If a bad outcome occurs, productivity is normalized to zero. When the good outcome occurs, one obtains the realized productivity of the job θ; hence, the expected productivity of the worker's effort is $\lambda\theta$. The cost of effort of the work is $V(\lambda)$, where the cost function satisfies $V(0) = 0, V' > 0$, $V'' > 0$ and $\lim_{\lambda \to 1} V(\lambda) = \infty$.

The firm cannot directly observe the effort λ, but rather it observes a signal correlated to λ. If the bad outcome occurs, it is assumed that both the worker and firm observe and agree upon this. If the good outcome occurs, then both the worker and firm receive noisy signals that this has occurred, formally given by $T = \{A, U\}$, where A denotes acceptable performance, and U denotes unacceptable performance. The problem is that the worker and the firm may not agree that the performance is acceptable. For example, the firm may believe that performance is acceptable and may reward the worker even though the worker feels that his performance is unacceptable.

Formally, let γ_{ts} be the probability that the signal pair ts is observed when the good outcome occurs, where t is the firm's observation, and s is the worker's observation. For example, γ_{UA} is the probability that, conditional upon the worker's effort being high, the firm believes effort is unacceptable, while the worker believes it is acceptable. This case can cause a problem, because the worker may believe that he is being unfairly treated when the firm does not reward him for good performance. It is exactly this type of situation that employment protection law tries to avoid. In the other cases, no problem arises - if the firm believes performance is acceptable and thus rewards the employee, the employee will not object regardless of his beliefs. Similarly, when both the employee and employer agree that performance is unacceptable, there are no grounds for conflict.

In practice, differences of opinion are inevitable, and hence it is reasonable to suppose that $\gamma_{UA} > 0$. MacLeod (2003) shows that as long as the evaluation for firm and *realized performance* are correlated, then it is possible to write a contract that provides performance incentives. However, the *cost* of providing incentives varies with the degree of correlation between the subjective evaluations of the firm and the worker. The optimal contract in fact requires the worker to impose a cost upon the firm whenever the firm believes performance to be unacceptable, while the worker feels that it is acceptable.

If there were no transactions costs and if effort were perfectly observable, then the wage of the worker in a competitive labor market would be:

$$w = w^0 + V(\lambda).$$

The work would be paid her market wage, w^0, plus a compensating differential, $V(\lambda)$, for the provision of effort λ. However, the firm cannot directly observe λ, but rather must use a subjective evaluation of performance. MacLeod (2003) shows that the asymmetric information due to the subjective evaluation introduces an additional deadweight cost:

$$C(\lambda, \alpha) = \lambda \alpha V'(\lambda), \tag{1}$$

where $\alpha = \frac{\gamma_{UA}}{\gamma_{AA}}$ is parameter that is called the *perceived bias*. The total cost to the firm of hiring a worker who provides effort λ and has a perceived bias of α is now given by:

$$\begin{aligned} W\left(w^0, \lambda, \alpha\right) &= w + C(\lambda, \alpha) \\ &= w^0 + V(\lambda) + C(\lambda, \alpha). \end{aligned}$$

In other words, the cost of using a subjective evaluation system is a function of the likelihood that the worker and firm disagree regarding acceptable performance. If they always agree, then there are no agency costs. The evidentiary requirements of the legal system encourage an objective evaluation of employee performance. The consequence is that a WDL is likely to lead to a *decrease* in α and hence to a lowering of enforcement costs.

The benefit of expression 1 is that it allows us to write a reduced form model of employment that nevertheless captures the consequence of subjective evaluation on employment costs. If the worker's *ex post* productivity is θ, then the expected profit of the firm that employs the worker is:

$$\begin{aligned} P^E\left(\theta, w^0, \alpha\right) &= \max_{\lambda \in [0,1]} \lambda\theta - W\left(w^0, \lambda, \alpha\right) && (2) \\ &= \max_{\lambda \in [0,1]} \lambda\theta - w^0 - V(\lambda) - C(\lambda, \alpha), && (3) \end{aligned}$$

which has the feature that $\partial P\left(\theta, w^0, \alpha\right)/\partial\alpha < 0$. Observe that the solution to (2), $\lambda(\theta)$, is an increasing function of θ, and hence observed worker wages rise with productivity, even though the worker's utility remains unchanged. If a worker is dismissed, then the profit of the firm is simply $-F$. Thus, the firm keeps the worker whenever $\theta \geq \theta^P$, where the cutoff productivity θ^P solves:

$$P^E\left(\theta^P, w^0, \alpha\right) = -F,$$

where we implicitly suppose that w^0 is such that $\theta^P \in (0,1)$. The profit function of a firm with productivity parameter θ^0 is:

$$\begin{aligned} P\left(\theta^0, w^0, F, \alpha, \pi\right) = \; & \pi \max\left\{-F, P^E\left(\theta^0, w^0, \alpha\right)\right\} + \\ & (1-\pi)\{\int_{\theta^P}^1 P^E\left(\theta, w^0, \alpha\right) g(\theta)\, d\theta \\ & -\left(1 - G\left(\theta^P\right)\right) F\} \end{aligned}$$

Total employment in period 1 is given by:

$$E\left(w^0, F, \alpha, \pi\right) = N\left(1 - G\left(\theta^A\left(w^0, F, \alpha, \pi\right)\right)\right),$$

where $G(\cdot)$ is the cumulative distribution function corresponding to $g(\cdot)$, and $\theta^A\left(w^0, F, \alpha, \pi\right)$ is the unique solution to:

$$P\left(\theta^A, w^0, F, \alpha, \pi\right)\begin{cases} < 0, & \text{for } \theta^A = 1, \\ = 0 & \text{for } \theta^A \in [0,1], \\ > 0 & \text{for } \theta^A = 0. \end{cases}$$

That is, for $\theta^0 \geq \theta^A\left(w^0, F, \alpha, \pi\right)$ the firm earns non-negative profits from hiring the worker given the optimal employment policy in period 2, (except when $\theta^A = 1$, in which no employment is efficient).

In the case of employment regulation, one typically assumes that w^0 represents the income when unemployed. Hence, it can be assumed to be exogenous and can be set such that there is an internal solution, with total employment less than the supply of labor. We can now determine the effect of a WDL. Let L denote the strength of employment protection legislation, with $\alpha(L)$ and $F(L)$ denoting the corresponding effects on perceived bias and on firing costs.

When this legislation is strengthened, our discussion implies a fall in perceived bias and an increase in firing costs:

$$\begin{aligned} \frac{d\alpha(L)}{dL} &< 0, \\ \frac{dF(L)}{dL} &> 0. \end{aligned}$$

We can now compute the effect that the law will have on employment via its effect on $\theta^A\left(w^0, F, \alpha, \pi\right)$ - if θ^A rises, then this corresponds to a decrease in employment and vice versa. For convenience, let $\theta^*(L) = \theta^A\left(w^0, F(L), \alpha(L), \pi\right)$; then when there is an interior solution then we have:

$$\frac{dP\left(\theta^*(L), w^0, F(L), \alpha(L), \pi\right)}{dL} = 0.$$

Therefore, we have:

$$\frac{d\theta^*(L)}{dL} \cdot \frac{\partial P}{\partial \theta^0} = -\left\{\frac{\partial P}{\partial \alpha}\frac{d\alpha(L)}{dL} + \frac{\partial P}{\partial F}\frac{dF(L)}{dL}\right\}. \tag{4}$$

It is straightforward to sign the various partial derivatives:

$$\begin{aligned} \frac{\partial P}{\partial \theta^0} &> 0, \\ \frac{\partial P}{\partial \alpha} &< 0, \\ \frac{\partial P}{\partial F} &< 0. \end{aligned}$$

From this we can see that that effect of a WDL upon employment is *ambiguous.* The increase in firing costs leads to a fall in profits and to lower employment. Conversely, the law decreases the perceived bias in employment relationships which increases performance.

The ambiguous effect of the law upon employment is consistent with the previous literature that either finds no effect or in some cases finds a negative effect. In particular, as Heckman and Pagés (2004) find, employment protection law has differential effects upon different categories of workers, with more negative effect upon younger workers and upon workers with more marginal attachments to the labor force. This is consistent with the current model. Notice that the magnitude of $\frac{\partial P}{\partial F}$ increases (is more negative) with an increase in variability of employment (π falls). If the size of $\frac{d\alpha(L)}{dL}$ is sufficiently small, then for high variability in worker productivity a WDL is predicted to have a negative effect upon employment.

Conversely, consider the case in which $\pi = 1$, and hence there are no productivity shocks *ex post*. In that case, firing costs have no effect, and one has the unambiguous result:

$$\left.\frac{dE\left(w^0, F\left(L\right), \alpha\left(L\right), \pi\right)}{dL}\right|_{\pi=1} > 0.$$

In this case, an increase in employment protection lowers the cost of eliciting effort λ. Thus, the level of effort, and hence the wage, $W\left(w^0, \lambda, \alpha\right)$, rise with employment protection. In summary, we find that for jobs with low turnover, increased employment protection increases wages and employment, while for jobs with high variability in productivity, one sees the opposite effect. We now turn to our identification strategy for testing these implications in our data.

3.1 Identification Strategy

In summary, when there is less variability in worker productivity, WDLs are likely to lead to higher employment and wages, with the converse when variability is high. Hence, the theory predicts that the effect of WDLs are likely to be ambiguous as a function of job characteristics, particularly the degree to which productivity fluctuates. However, we cannot directly measure worker productivity.

Rather, we have data on the amount of investment in worker training by occupation. This data was collected before our period of interest, and hence the levels of investment reported are independent of the changes in legal regime. We use this data to divide jobs into high, medium and low levels of investment. Given that more training is associated with longer tenure and lower turnover, we would expect that the effect of the law is likely to be negative for occupations with low investment and possibly positive for occupations that entail more investment.[14]

Formally, we can see this as follows. Suppose, as in Jovanovic (1979), the market is perfectly competitive, and hence the worker internalizes all of the benefits and costs from investment. In other words, it makes no difference whether the worker or the firm makes the training decision - the final outcome is efficient with the employment contract allocating the costs and benefits. An investment i in worker training results in realized productivity $\theta^0 + \delta$ with probability π, and θ with probability $(1 - \pi)$, where $\delta > 0$. The idea is that this investment can be seen as task specific, and hence an increase in variability in production reduces the benefits from investment. One can be more general than this, but it would not alter our basic identification strategy. The benefit is that we can use our results above to easily derive the optimal training strategy.

Investment in worker training occurs if and only if:

$$P\left(\theta^0 + \delta, w^0, F, \alpha, \pi\right) - i \geq P\left(\theta^0, w^0, F, \alpha, \pi\right).$$

Since $\frac{\partial^2 P}{\partial \pi \partial \theta^0} > 0$, it follows that, holding all else fixed, an increase in π (decrease in turnover) results in a relaxation of this inequality. Hence, jobs with high investments are associated with low levels of worker turnover. Thus, we predict that the effect of WDLs are likely to have a more positive effect on workers

[14] See Farber (1999) for a review of the effects of worker training on job tenure.

with higher levels of investment into skills, while it has a negative effect on the employment of workers with low levels of investment.

The effect on wages is theoretically difficult to determine because the starting wage depends upon the structure of the employment contract. For example, the same amount of expected lifetime income can be achieved with quite a bit of variation on how compensation is allocated between wages, severance pay and retirement savings. We do not observe these variables in the data, and we do not know how they might change in response to changes in the law.

4 Data

The main data source for our study is the Current Population Survey (CPS). The CPS is the monthly labor force survey conducted by the U.S. Bureau of Labor Statistics. The purpose of the survey is to measure labor force participation and employment and to produce estimates of labor force characteristics of the U.S. civilian non-institutional population aged 16 and older. About 60,000 households (approximately 100,000 adults) are interviewed each month. The CPS has a 4-8-4 rotation group structure. Households are interviewed consecutively for four months and are left out of the sample for eight months. The households are again interviewed for another four consecutive months and are then left out of the sample permanently. The earning questions are asked to only one-fourth of the workers in the survey each month. These are the workers in their fourth and in their eighth months of the interviews (i.e., they are in the outgoing rotation groups).

The CPS is composed of the Basic Monthly Surveys and the Supplements. The Basic Monthly Surveys ask questions about labor force status and basic demographic information. In addition to the Basic Monthly Surveys, occasionally, the CPS includes supplemental questions on subjects of interest to federal and state agencies, to private foundations, and to other organizations. Questions in the CPS supplements vary. Existing supplements include topics such as job training, job tenure, contingent employment, worker displacement, veteran status, school enrollment, immigration, fertility, voting, smoking, computer usage, health, and employee benefits. Questions in the Basic Monthly Surveys and in the Job Training Supplements are of interest to us and will be utilized in this paper.

We use the CPS basic monthly files from 1983 to 1994 to construct the employment and the wage data series for our regression analysis. There are two reasons why we start our data series in 1983 and not earlier. First, the 2-digit detailed occupation codes that we need to use in our study changed over the period. More specifically, before 1983, the CPS follows the 1970 census for the detailed occupation codes, but from 1983 until 2002 the CPS follows those of the 1980 census. These codes cannot be directly converted without introducing some inaccuracies due to the imputation.[15]

Secondly, we use the CPS Job Training Supplement questions conducted in January 1983 to categorize the investment characteristics of different occupations.[16] By starting our data series after January 1983, we have training levels defined *before* the period that we study the law changes, and hence these categories are not affected by these law changes. We use these questions in calculating the average amount of training obtained in each occupation and in classifying occupations into three groups, namely low-, medium-, and high-investment occupation groups. Although one may argue that levels of training may change for some occupations once WDLs are introduced, an assumption we make here is that the high-investment occupations will still be associated with higher levels of training than those associated

[15] The 2-digit detailed occupation codes are the grouping of the 3-digit ones. There is no one-to-one relationship between the 1970 census occupation codes and the 1980 census occupation codes. The 1980-census-3-digit codes can be imputed from the 1970 ones and vice versa (See U.S. Bureau of the Census Technical Paper 59). However, imputation will inevitably introduce some inaccuracies. Thus, we decide not to do it here.

[16] The CPS Job Training Supplement questions were also asked in January 1984 and in January 1991.

with the medium- and the low-investment occupations. We assume that the medium-investment occupations will still be associated with higher levels of training than those associated with the low-investment occupations. In other words, we assume that each occupation will not be re-categorized into other categories once the laws are introduced.[17]

The CPS Job Training Supplements gather detailed information about the training that workers needed to obtain to earn their jobs and about the training that workers received to improve their skills once on those jobs. More specifically, we are interested in the questions regarding the training which full-time workers received after obtaining their current jobs. Such questions are as follows:

1. SINCE YOU OBTAINED YOUR PRESENT JOB, DID YOU TAKE ANY TRAINING TO IMPROVE YOUR SKILLS? (YES, NO, N/A)
2. (IF YES TO THE PREVIOUS QUESTION): DID YOU TAKE THE TRAINING IN:
   (a) A SCHOOL? (YES, N/A)
      i. (IF YES TO THE PREVIOUS QUESTION): DID YOUR EMPLOYER PAY FOR THE TRAINING? (YES, NO, N/A)
   (b) A FORMAL COMPANY TRAINING PROGRAM? (YES, N/A)
   (c) INFORMAL ON-THE-JOB TRAINING? (YES, N/A)

From the survey questions, we cannot clearly identify whether the training that the worker received was general or specific.[18] However, in general if the labor market is competitive, then we expect the firm to pay for any relationship specific investments, while the worker would pay for general training.[19] Even so, in terms of the predicted impact of the law, workers with greater investments have longer tenure, so we would expect employment protection to have a more positive effect in any job for which there is additional training. With the above training information, we can calculate, for each occupation, the following:

1. Fraction of workers who received any kind of training (any training criterion)
2. Fraction of workers who received employer paid school training (school training criterion)
3. Fraction of workers who received formal company training (formal training criterion)
4. Fraction of workers who received informal on-the-job training (informal training criterion)

These are four types of criteria of *investment* . It is worth noting that the universe of the Job Training Supplements contains the employed workers (both at work and not at work) and the unemployed workers who have worked in the past. Question 1 (above) is asked only to the employed workers who are at work. To calculate the fraction of workers who received any kind of training, we count the number of workers who answer YES divided by the number of workers who respond to the question by answering YES or NO[20] (i.e., we exclude the non-responses). For questions 2-a, 2-b, and 2-c, we can only identify whether the respondents answer YES to the questions. We cannot distinguish between NO and non-response, so we treat both to be NO. The fractions are the count of the number of workers who answer YES to the

[17] We use the January 1991 Job Training Supplement to verify this and find that the grouping of the occupations changes very little.

[18] According to Becker (1975), general training improves workers' skills that are useful anywhere. Specific training improves workers' skills that are useful only at current employer.

[19] See Parent (2000) for some evidence in support of this hypothesis as predicted by the model of MacLeod and Malcomson (1993).

[20] We use the January supplement weight (adjusted for supplement noninterviewed) in calculating the fractions.

question divided by the number of workers who respond to question 1.[21] We suppose that the fractions we calculate are acceptable approximates of average intensity of the training generally acquired by employees in each occupation.

The rankings of the occupations by each of the above criteria are illustrated in Table 2 (2A, 2B, 2C, and 2D). According to the rankings, occupations are classified into groups of high, medium, and low investment. In Table 2A, occupations are ranked using the any training criterion. Observe that there is a great deal of variation in the level of training, ranging from more than 70% in the case of high school teachers and health diagnostic technicians to 5% in private household service workers. In Table 2B and 2C, occupations are ranked by the school training and by the formal training criteria respectively. With only a few exceptions, the rankings by these three criteria (any training, school training, and formal training) are quite similar. Examples of occupations classified as low investment are private household service workers, cleaning and building service workers, motor vehicle operators, equipment cleaners, machine operators, and construction laborers. These occupations are generally low-skilled and do not require much education. On the other hand, for the high-investment group, occupations are generally high-skilled and require at least some college education. Examples of these are engineers, mathematical and computer scientists, health technologists, health diagnosing technicians, and natural scientists. Examples of medium-investment occupations are secretaries, computer equipment operators, mechanics, and repairers.

In Table 2D, occupations are ranked by the informal training criterion. The grouping of occupations under this criterion is very different from that of the first three criteria. It will be interesting to see if this variable provides any useful information given the subjective nature of the interpretation and the response to the informal training question.

In occupations associated with higher investment, we expect longer employment relationships between workers and employers. Our expectation is supported by the data from the January 1987 CPS Job Tenure Supplement. Table 3 illustrates average tenure (months consecutively working for current employer) by occupation groups categorized by the any training criterion. Of all 50 states, we observe that average tenure for the high-investment group is longer than that of the low-investment group in 46 states. Although we find about 25 states that have the exact order of the longest average tenure for high-investment and the lowest average tenure for low-investment (where average tenure for the medium group is exactly in the middle), we only have 1 state that has the exact opposite order. Also, in 30 states, high-investment occupations have longer average tenure than medium-investment occupations, and in 44 states, medium-investment occupations have longer average tenure than low-investment occupations. Rosen (1968) also documents empirically using the data on class-I railroad workers in the U.S. that workers who have higher specific investment by firm generally have lower employment variation than workers with lower specific investment.

In preparing the monthly employment data, we calculate each occupation group's employment in each state divided by the state population. The occupation questions are asked to the people in the labor force and to the people who are not in the labor force but who have worked prior to the time of the interview. Thus, a number of observations are missing information on occupations due to the fact that these people are not asked about their occupations. They are still, however, considered population of the states, so we include them in our denominator along with the unemployed and with people not in the labor force when calculating each occupation group's employment per state population. Our monthly employment data series run from February 1983 until December 1994, keeping the January 1983 training information exogenous from our regression. In preparing the data for the wage regressions, we calculate the average real wage for each occupation group by state. Our monthly wage data series also start in February

[21] We do this so that the workers taken into account for calculating the fractions (2), (3), and (4) are consistent with the workers taken into account for calculating fraction (1). Note that the workers who answer NO to question 1 are not asked question 2-a, 2-b, and 2-c, but they would have answered NO to these questions anyway.

1983 and end in December 1994.

5 Empirical Methodology

As Krueger (1991) and Dertouzos and Karoly (1992) have pointed out, the adoption of WDLs may not be completely exogenous. Situations that happened in each state and also each state's characteristics may have driven the adoption of the laws. However, Autor, Donohue, and Schwab (2004) observe that unless one can find some valid instruments to address the problem, the instrumental variable estimation will bias the estimates. In this paper, we address the possibility of endogenous adoption decisions by including state fixed-effects and state-specific time trends (along with time fixed effects) in our regressions. These variables capture the unobserved state characteristics that change over time and may be correlated with the state's decision to adopt the laws. In our analysis, we use case law classification of WDLs (identification of WDLs adoption dates) developed by Autor, Donohue, and Schwab (2006).[22]

To study the effects of the laws on employment of each occupation group, we employ the following model:

$$\begin{aligned}\ln(y_{jst}) \quad = \quad & \alpha + \eta' x_{jst} + \beta_1 \cdot Adopt_{st} + \beta_2 \cdot Adopt_{st} \times Low_j + \beta_3 \cdot Adopt_{st} \times High_j \\ & + Low_j + High_j + Low_j \times t + High_j \times t + \delta_t + \pi_s + \pi_s \times t + \epsilon_{jst} \qquad (5)\end{aligned}$$

where y_{jst} is occupation group j's employment per state s population at time t (month-year). x_{jst} is the vector of observable characteristics of each occupation group. These characteristics are a fraction of male workers, a fraction of black workers, a fraction of workers in each age group (18-35, and 36-55), a fraction of married workers, a fraction of unionized workers, and a fraction of workers in each education group (high school graduates, some college, and college education or higher). $Adopt_{st}$ is the dummy indicating whether the state is currently adopting the law. This dummy is set to 1 starting the month right after the initial adoption. Low_j and $High_j$ are the dummies denoting whether the observation belongs to the low-investment or the high-investment group, respectively. These dummies will capture the employment level difference between the high-investment occupations and the low-investment occupations (relative to the medium-investment occupations).

Observing the model, the effect of the laws on employment of the medium-investment group will be shown by the coefficient of the $Adopt_{st}$ variable (β_1) where the effects of the laws on employment of the low-investment and the high-investment groups are explained by $\beta_1 + \beta_2$ and $\beta_1 + \beta_3$, respectively. One may argue, according to the U.S. labor market experience over our data period, that the high-skilled sector may have been expanding, and the low-skilled sector may have been contracting. If that is the case, then our sector-specific time trends ($Low_j \times t$ and $High_j \times t$) should capture such phenomena. We should expect to see a negative and significant coefficient for the low-investment-occupation-group trend and a positive and significant coefficient for the high-investment-occupation-group trend.

The δ_t's, and π_s's are time fixed effects and state fixed effects, while the $\pi_s \times t$'s are the state-specific time trends. We will do our regression analysis for each type of WDL for each investment criterion. We also run the regressions with and without the set of group controls (x_{jst}'s).

The effects of WDLs on each occupation group's average wage are estimated using the following model:

[22] As mentioned earlier, this information is summarized in Table 1.

$$\ln(w_{jst}) = \alpha + \eta' x_{jst} + \beta_1 \cdot Adopt_{st} + \beta_2 \cdot Adopt_{st} \times Low_j + \beta_3 \cdot Adopt_{st} \times High_j + Low_j + High_j + Low_j \times t + High_j \times t + \delta_t + \pi_s + \pi_s \times t + \epsilon_{jst} \quad (6)$$

where w_{jst} is the average real wage for occupation group j in state s at time t (month-year). Other variables included in this model are analogous to the ones included in the employment model. Similarly, the effects of the laws on the average wage for the medium-investment group are captured by β_1. The effects of the laws on the average wage for the low-investment and the high-investment group are captured by $\beta_1 + \beta_2$ and $\beta_1 + \beta_3$ respectively. Now, the sector-specific trends ($Low_j \times t$ and $High_j \times t$) will capture whether wages in each sector have evolved trend-like over time. As performed with the employment analysis, we will examine the effects of each type of WDL under each criterion of investment separately, with and without the occupation group controls (x_{jst}'s).

We use the weighted least square procedure in our analysis. The reason for weighing is to achieve some efficiency gain since the cell-mean data are used as the dependent variables. Thus, the error terms are suspected to be heteroskedastic. The employment regression is weighed by the square root of the number of observations that belong to each occupation group in each state. For the wage regression, we use the square root of the number of observations that belong to each occupation group in each state that have valid wage information (number of observations used to compute the average wage value in each occupation group-state cell) as the weight.

As Bertrand, Duflo, and Mullainathan (2004) have pointed out, we cannot reject the possibility that the error terms of our data series (both employment and wage) are serially correlated. The serial correlations will make the standard errors calculated by the usual method biased towards zero. Therefore, we cluster our standard errors by state (Huber-White robust standard errors) to allow such possible correlation of the error terms over time and within state. We assume that the error terms in different states are independent.

6 Results

6.1 Good Faith Exception to Employment At-Will

Table 4 reports the effect of the good faith exception upon employment (Table 4A) and upon wages (Table 4B) using each of the four criteria of investment. Starting with the employment results in Table 4A, the first two columns are the results when the any training criterion measure of investment is used. The effect of good faith on employment of the medium group (*Adopt*) is positive and significant at the magnitude 4.8% in the model without occupation group controls (Column 1). The effect remains significant, but the magnitude is reduced to about 3.1% when the occupation group controls are included (Column 2). The effect of the law on employment of the low-investment group relative to the medium-investment group (*Adopt* $\times$ *Low*) is negative and significant. The magnitude is 15.3% without the controls and reduces to 10.6% with the controls. The overall effect of good faith on the low group is illustrated by *Adopt* + *Adopt* $\times$ *Low*. The T statistic is significant at 1% when no characteristic control is included and the significance reduces to 5% when the controls are included. With the controls, the good faith exception reduces the employment of the low-investment occupation group by approximately 7.5%. The magnitude is 10.6% in the model without controls. For the high-investment group, good faith has an overall positive and significant effect on employment. The magnitude is 11.4% in the model without the controls and 12.7% in the model with the controls.

Looking at the coefficient of each group's dummy and each group's time trend, we observe a negative and significant (at 1%) coefficient for $High$. This means that the high-investment occupation group is generally *smaller* than the medium- and the low-investment groups. The coefficient for *Low* is not significant; therefore, the sizes of the low group and the medium group are not significantly different. The negative coefficient of the low-investment-group time trend ($Low \times t$) and the positive coefficient of the high-group time trend ($High \times t$) are very significant (at 1%) as expected. This supports our earlier argument that we expect the low-investment sector to contract and the high-investment sector to expand over our data period. Other characteristic controls that have significant coefficients do not have unexpected signs.

Column 3 and Column 4 display the regression results when the school training criterion is used to categorize the occupations into groups. The results under this criterion show no significant effects of good faith on the employment of the medium group. The overall effects of the law on the employment of the low-investment group are negative at the magnitude of 9.6% in the model with controls and 11.7% in the model without controls. On the other hand, the good faith law is associated with the increase in the employment of the high-investment group at the magnitude of 14.5% in the model with controls and 14.6% in the model without controls.

The results under the formal training criterion are illustrated in Column 5 and in Column 6. There, we again observe the positive effects of good faith on the employment of the high- and the medium-investment occupation groups, and we observe the negative effects of good faith on the employment of the low-investment occupation group. Good faith reduces low-investment occupations' employment by about 7.1% in the model with controls and 10.2% in the model without controls. On the other hand, good faith increases medium-investment occupations' employment by about 3.4% in the model with controls and 4.2% in the model without controls, and it increases high-investment occupations' employment by about 6.5% in the model with controls and 10.5% in the model without controls.

On the other hand, under the informal training criterion (Column 7 and Column 8), we find no significant effects of good faith on employment of any group. This is probably because the respondents' answers to the informal training question are spurious. Compared to other questions regarding training, the informal training question is less clear in the sense that the respondents may not be given a definition of informal training. For example, some may interpret that learning-by-doing in the workplace is considered informal training, but others may not believe so. Therefore, the classification of occupations into groups under this criterion may not be a reliable method to quantify investment.

Looking at the joint test of significance of all of the adoption variables ($Adopt = Adopt \times Low = Adopt \times High = 0$), we can reject the null hypothesis that these variables are not significant at 11.9% for the first three criteria. However, under the informal training criterion, the F statistics are quite small and we cannot reject the null.

Now, we turn to the visual illustration of employment per population of the low-investment and of the high-investment groups in the states that adopted good faith during our data period. Figure 3 demonstrates such graphs where occupation groups are categorized using the any training criterion. Across all 7 states (Alaska, Arizona, Delaware, Idaho, Nevada, Oklahoma, and Wyoming), we observe that the low-investment group constitutes a *larger* sector compared to the high-investment group. We observe small negative trends for the employment per population of the low-investment group and small positive trends for that of the high-investment group in some states. As mentioned earlier, these trends are captured by the variables $Low \times t$ and $High \times t$ in our model. From our results, we still observe very large and very significant effects of good faith even though the adoption of good faith only occurred in seven states during our data period. Thus, the good faith law itself must have some considerable impacts on the employment relationships in the U.S. labor market.

Table 4B reports the effects of the good faith law on wages. Across all criteria of investment, we do not observe any significant effects of the law on wages.[23] We observe that low-investment occupations are associated with lower wages and that high-investment occupations are associated with higher wages (negative and significant coefficients for *Low* and positive and significant coefficients for $High$). Except for the informal training criterion, we observe positive and significant trends for wages of the high-investment group, and negative and significant trends for wages of the low-investment group. This probably illustrates the higher demand and the increased return in the high-skilled sector over the period.

In most models (all except Column 4), the joint F-tests of the adoption variables illustrate that we cannot reject the null hypothesis that these adoption variables are insignificant.

To conclude, most of the point estimates indicate a positive employment effect of the law for high-investment occupations and a negative employment effect for low-investment occupations. The effect on wages is very small and hardly significant. Under the assumption that the market is competitive, these results combined with the employment results suggest an overall negative effect of the law for low-investment occupations and positive welfare for high-investment occupations.

6.2 Implied Contract Exception to Employment At-Will

Table 5 reports the results of the effects of the implied contract exception. Observing the effects on employment in Table 5A, we find a negative effect of the law on the employment of the low-investment group (5.9%) under the any training criterion. The effect is, however, no longer significant once the occupation group characteristic controls are included. Under the school training criterion, we observe a small negative effect of the law on the employment of the medium-investment group. The magnitude is 2.6% in the model without controls. The negative effect remains significant once the controls are included, and the magnitude *increases* to 3.6%. We also observe a positive effect on the employment of the high-investment occupation group. The magnitude is 5.3% without controls, but the effect is no longer significant when we include the controls. The informal training criterion shows some negative effects of the law on the employment of the medium-occupation group. The magnitude is 4.1% in the model without the controls and 3.0% in the model with the controls.

As observed in the results of the good faith law on employment, we generally observe positive and significant trends for the high-investment occupations and negative and significant trends for low-investment occupations. Except for the model using formal training criterion with controls and the model using informal training criterion with controls, we can reject the null hypothesis that all the adoption variables are insignificant (at 10%).

Table 5B reports the effects of the implied contract law on wages. Under the any training and school training criteria, we observe some limited evidence of positive wage effects. Under the any training criterion, we observe 0.8% (only 10% significant) increase in wage of the medium group in the model where characteristic controls are included (Column 2). Under the school training criterion, we observe 1.2% (only 10% significant) increase in wage of the high group in the model where characteristic controls are included (Column 4). Under the formal training criterion, we also observe 1.0% increase in wage (significant at 10%) of the medium group in the model without controls, and the effect is 1.3% (significant at 5%) when the controls are included.

Again, we observe positive and significant trends for wages of the high-investment sector and negative and significant trends for wages of the low-investment sector. This is true across the first three criteria of investment. The joint significant F test values (the null hypothesis is that all the adoption

[23] besides the 10% significant effects on the medium group's wage under the school training criterion (Column 3) and under the formal training criterion (Column 5), both of which are no longer significant once the occupation group characteristic controls are included in the models.

variables are zero) are large only for some model (Column 1, Column 5, Column 6, Column 7, and Column 8), thus we can only reject the null hypothesis under these models.

6.3 Public Policy Exception to Employment At-Will

The results from the good faith and from the implied contract exceptions have suggested, at some level of precision, that the employment of the high-investment group is positively affected by the laws and that the employment of the low-investment group is negatively affected by the laws. We have already argued that our sector trend variables would help to capture the episodes of the contraction of the low-skilled sector and of the expansion of the high-skilled sector during our data period, and thus our coefficients of the adoption variables must have been accurate measures of the effects of the laws and not the illustration of the trends.

As we discussed above, the public policy exception is not intended to remediate the efficiency of the employment relationship, but rather it restricts the actions of employers to protect existing public policy. As shown in Figure 1 and in Figure 2, many states adopted this type of exception during our data period. The group of states that adopted the public policy rule is similar to the group that adopted the implied contract rule. Table 6A shows that the law has virtually no effect on the employment of the low- nor of the high-investment groups (this is true across all criteria of investment). We obtain a similar result for wages, as shown in Table 6B.

These results act as a control for the employment results from the good faith and the implied contract exceptions. Basically, if the results from the above sections are spurious correlations with employment trends of the low-investment and high-investment occupations, then we should observe similar patterns here. Since we do not, this would lend additional support to the hypothesis that the good faith and implied contract exceptions enhance the employment of the high-investment occupations and reduce the employment of the low-investment occupations.

7 Additional Results for Good Faith and Implied Contract

We further question whether the effects of the laws are different in highly populated areas from those in less populated areas. In highly populated areas, labor markets are more competitive, and hence there is likely to be more turnover for all types of workers. As a consequence, the effect of the law is likely to be more negative. Moreover, in a more competitive environment, there are fewer rents. Therefore, firms with poor management are more likely to be selected out by the market, which would further attenuate any positive effects of employment protection.

In contrast, in low population areas labor is more scarce, and the idiosyncratic match component is likely to be larger. Moreover, with less competition, there would be less selection against poor management and hence a greater scope for the law to enhance productivity. This suggests that we should observe variations in the impact of these laws depending upon whether one is in a rural or urban area.

We explore this by first restricting the sample to highly populated areas as defined by the Standard Metropolitan Statistical Area (SMSA) with population one million or more for our 1983 and 1984 data and to the areas belonging to the Metropolitan Statistical Area (MSA) with population one million or more for our 1985 data onwards. This complexity is due to the change in the definition of metropolitan area defined by the Office of Management and Budget (OMB) over the period. We show graphically the states that contain the highly populated areas in Figure 4. The results of the effects of the laws by areas are discussed below.

7.1 Good Faith Exception to Employment At-Will

Table 7A shows the results of the effects of the good faith exception on employment in highly populated areas.[24] There, we observe some positive effects of the law on the employment of the high-investment occupation group when the school training criterion is used. The positive effect is about 5.7% (significant at 10%) in the model without the controls and such effect increases to 6.5% (significant at 5%) when the controls are added. We observe some negative effects of the law on the employment of the low-investment occupation group when the informal training criterion is used. The magnitude is 4.2% when no controls are added, and the magnitude becomes 4.6% when the controls are added. There seem to be no effects of the law on the employment of the medium group.[25]

Table 7B illustrates the wage effects in highly populated areas. Across all measures of investment, we observe negative wage effects for *all* groups of occupations. When the any training criterion is used, the magnitude of the negative effect is 6.6% for the low-investment group, 5.2% for the medium-investment group, and 4.0% for the high-investment group in the model with controls. In the model without controls, only the negative effect for the low-investment group is significant (the magnitude is 4.1%). When the school training criterion is used, the magnitude of the negative effect is 6.5% for the low-investment group, 3.8% for the medium-investment group, and 3.4% for the high-investment group in the model with controls. In the model without controls, only the negative effect for the low-investment group is significant (the magnitude is 4.1%). Under the formal training criterion, the magnitude of the negative effect is 5.7% for the low-investment group, 3.9% for the medium-investment group, and 3.9% for the high-investment group in the model with controls. In the model without controls, only the negative effect for the low-investment group is significant (the magnitude is 3.0%). For the informal training, the negative effect is 4.1% for the low group, 4.6% for the medium group, and 3.9% for the high group in the model with controls (no significant results in the model without controls).

The effects of the good faith exception in less populated areas (population less than 1 million) are illustrated in Table 8. For employment (Table 8A), we observe similar pattern across all models except for the ones using the informal training criterion. We see positive employment effects for the high-investment group and negative employment effects for the low-investment group. The magnitudes of the negative effects vary between 9.7% (formal training criterion with controls) to 12.1% (school training criterion without controls). The magnitudes of the positive effects vary between 10.2% (formal training criterion with controls) to 15.5% (school training criterion without controls). We also find some positive effects for the medium-investment group when the any training and the formal training criteria are used. The magnitude is 4.4% for the any training criterion with controls (4.2% without controls) and 4.1% for the formal training criterion with controls (3.8% without controls).

Table 8B illustrates the wage effects of the good faith exception in less populated areas. There, we observe some positive significant wage effects for the medium investment group. The magnitude ranges from 1.5% (any training with controls) to 2.9% (informal training without controls).

In sum, the effects of the good faith exception on employment in highly populated areas and in less populated areas seem to be consistent with our employment results in the previous section (overall area). The results from less populated areas, however, seem to show a clearer pattern of positive employment effects for the high-investment occupations and negative employment effects for the low-investment occupations. The effects on wages are, however, different by areas. In the previous section, we observe virtually no effects on wages in overall area. In this section, we find *negative* wage effects in highly

[24] Among seven states (Alaska, Arizona, Delaware, Idaho, Nevada, Oklahoma, and Wyoming) that adopted the good faith exception during our data period, only two states (Delaware and Arizona) contained highly populated areas.

[25] The 10-percent-significant positive effects in Column 5 and in Column 7 are no longer significant once the controls are added.

populated areas for *all* occupation groups. For less populated areas, we find some evidence of *positive* wage effects for some occupation group.

This suggests that the law has a more negative effect in the more highly populated areas, as we predicted above.

7.2 Implied Contract Exception to Employment At-Will

Table 9A provides the estimated impacts of the implied contract exception on employment in highly populated areas. Again, we observe a clear pattern of negative employment effects for the low-investment occupation group across all four criteria of investment. The magnitudes of the effects range from 4.8% (informal training without controls) to 8.0% (any training without controls). The positive employment effects for the high-investment occupations are observed only under the school training criterion. The magnitude is 4.9% in the model without controls and 5.2% in the model with controls. The negative employment effects for the medium-investment group are found under the any training criterion at the magnitude of 2.6% (without controls) and under the school training criterion at the magnitude of 4.9% (with and without controls).

The wage effects of the implied contract exception in highly populated areas are shown in Table 9B. We find some negative wage effects for the low-investment occupation group. The magnitude is 2.4% under the school training criterion (with controls) and 1.8% under the formal training criterion (with controls). However, we find no wage effects for other occupation groups.

For less populated areas, the employment results are illustrated in Table 10A. We observe no clear pattern for the impact of the law on employment. Under the school training criterion, we find negative impacts of the law on the medium-investment group's employment. The magnitudes are 3.2% (without controls) and 3.5% (with controls). The informal training criterion gives bizarre estimates of positive employment effects for the low-investment occupation group and of negative employment effects for the high-investment occupation group; although, these are no longer significant when the controls are included. This is probably consistent with our earlier expectation that the informal training question does not provide a good measure of investment.

Table 10B shows the impacts of the law on wages in less populated areas. We find some limited positive effects of the law on the wages of the low-investment occupation group. The effects are, however, no longer significant once the controls are included. We also find some positive significant wage effects on the wages of the medium-investment occupation group under the informal training criterion (2.3% without controls, and 1.7% with controls).

In sum, similar to the results found in the previous section (implied contract law in overall area), the positive employment effects for the high-investment group and the negative employment effects for the low-investment group are also found in highly populated areas. For wages, we find some evidences of the negative effects of the law in highly populated areas and find some limited evidence of the positive effect of the law in less populated areas.

8 Concluding Discussion

The question we have addressed in this paper is whether or not there are any beneficial effects from the introduction of exceptions to employment at-will. The traditional economic view supposes that, in a competitive economy, employers and employees write the contracts that they intend, and hence there can be no role for the courts beyond enforcing the agreements as written.

The view from the court room is rather different. There, we see disputes between disgruntled employees and employers who are not always exemplary in either their behavior or in their ability to properly manage their employees. If these cases are simply extreme and unusual situations, then we would not expect the introduction of new legal default rules to have much effect. The good faith exception is primarily aimed at requiring employers to compensate employees as they have agreed and not try to dismiss employees in an opportunistic fashion. For this law, we find consistently positive employment effects upon the employment of skilled workers.

The economic consequences of the implied contract exception are less clear since the law does not always provide clear criteria for either the existence of a long term contract or for what exactly constitutes a just cause. However, even given the apparent vagueness of the rule, we find that in some cases it has a positive effect on highly skilled workers, though - as with the good faith rule - the effect for low skilled occupations is negative. It is interesting to note that we find no effect of the public policy exception upon employment for the full sample, suggesting that the effect of the law change is not simply a correlation with employment growth.[26]

Our results are consistent with earlier evidence that finds that changes in employment law have either a negative or small effect. The new point here is that for some occupations the effect may in fact be positive. These results are of course quite preliminary. If they are confirmed by future research, they suggest that exceptions to employment at-will should depend upon the extent of the employee's investment in job specific skills. These results are consistent with the view that the common law evolves to find efficient solutions to cases that are adjudicated in court (see Posner (2003)).

The results also provide some much needed evidence for the debate on the role of legal defaults in contract law. The standard presumption in law and in economics is that rational parties write contracts best suited for their situation, and hence there is a limited scope for legal intervention beyond merely enforcing the contract as written (see for example the excellent paper by Schwartz and Scott (2003)). There is very little empirical work that explicitly addresses this important issue. Our empirical results suggest that courts can, under the appropriate conditions, enhance the operation of the marketplace, particularly when markets are not perfectly competitive.

[26] We ran the regressions exploring the effect of the public policy exception for high and low population areas. There we found a negative effect upon employment in only the high population areas, a result that is consistent with earlier work.

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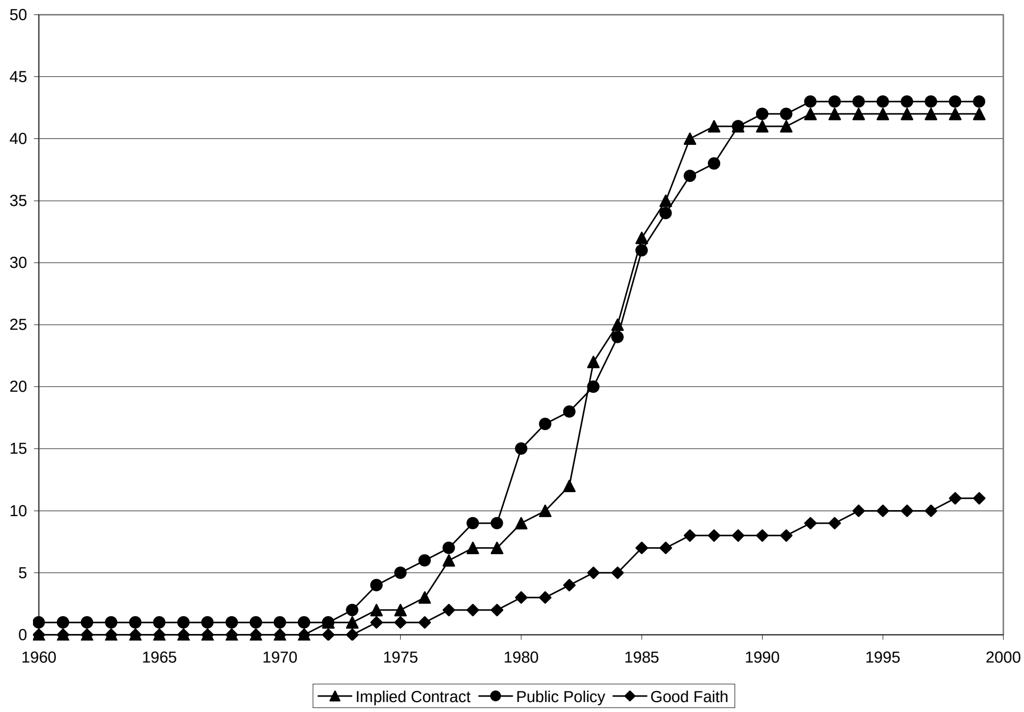
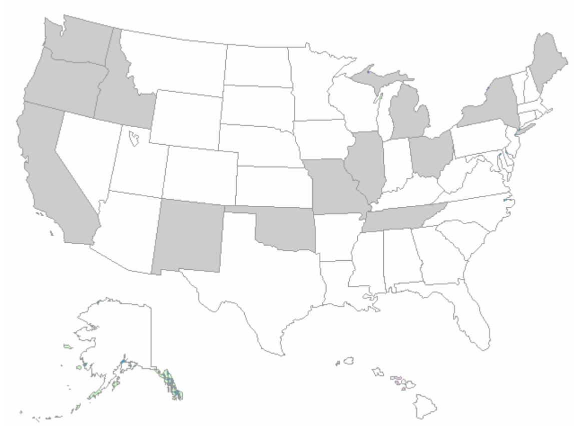
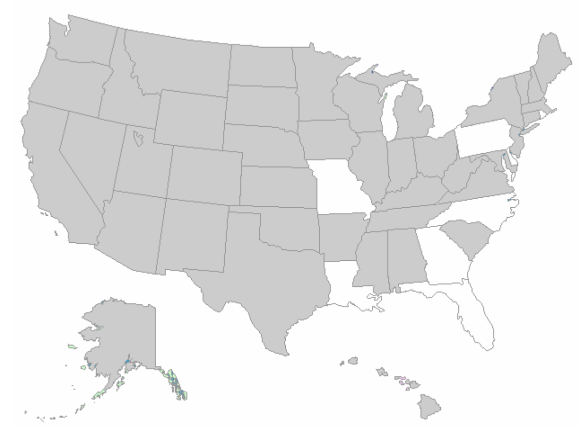
Figures and Tables

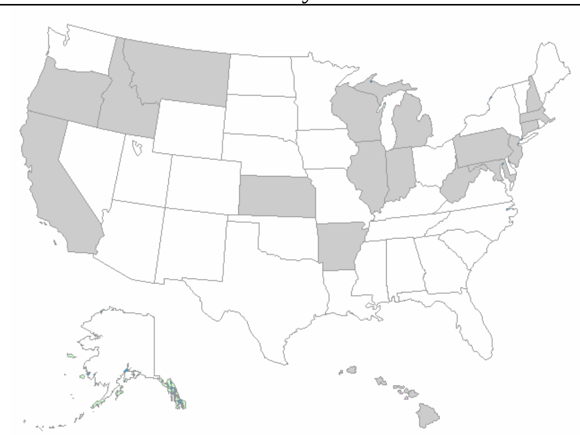
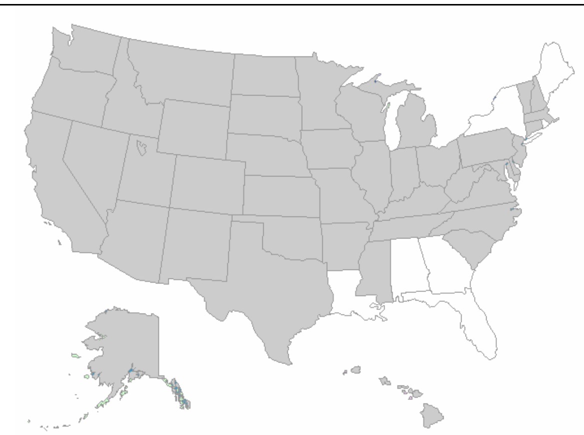
Figure 1: Number of States Adopting at-will Exceptions



Source: Illustrated from Autor, Donohue, and Schwab (2006)'s Legal Appendix

Figure 2: Pattern of Adoption during 1983-1994

Implied Contract Exception February 1983	Implied Contract Exception December 1994
	

Public Policy Exception February 1983	Public Policy Exception December 1994
	

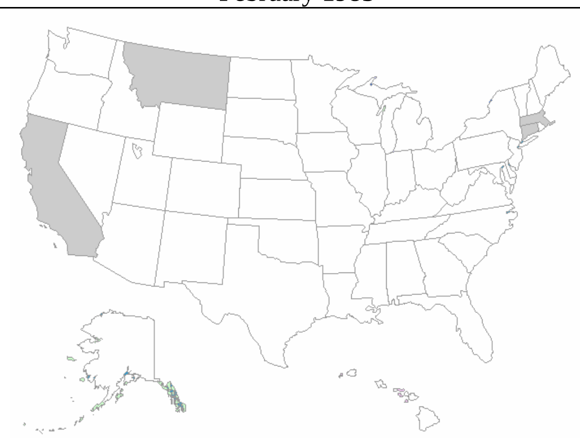
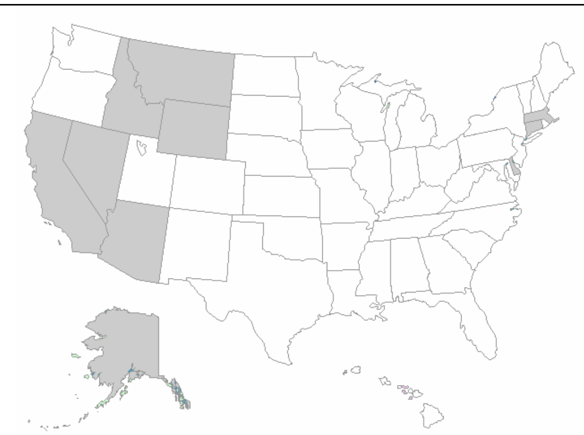
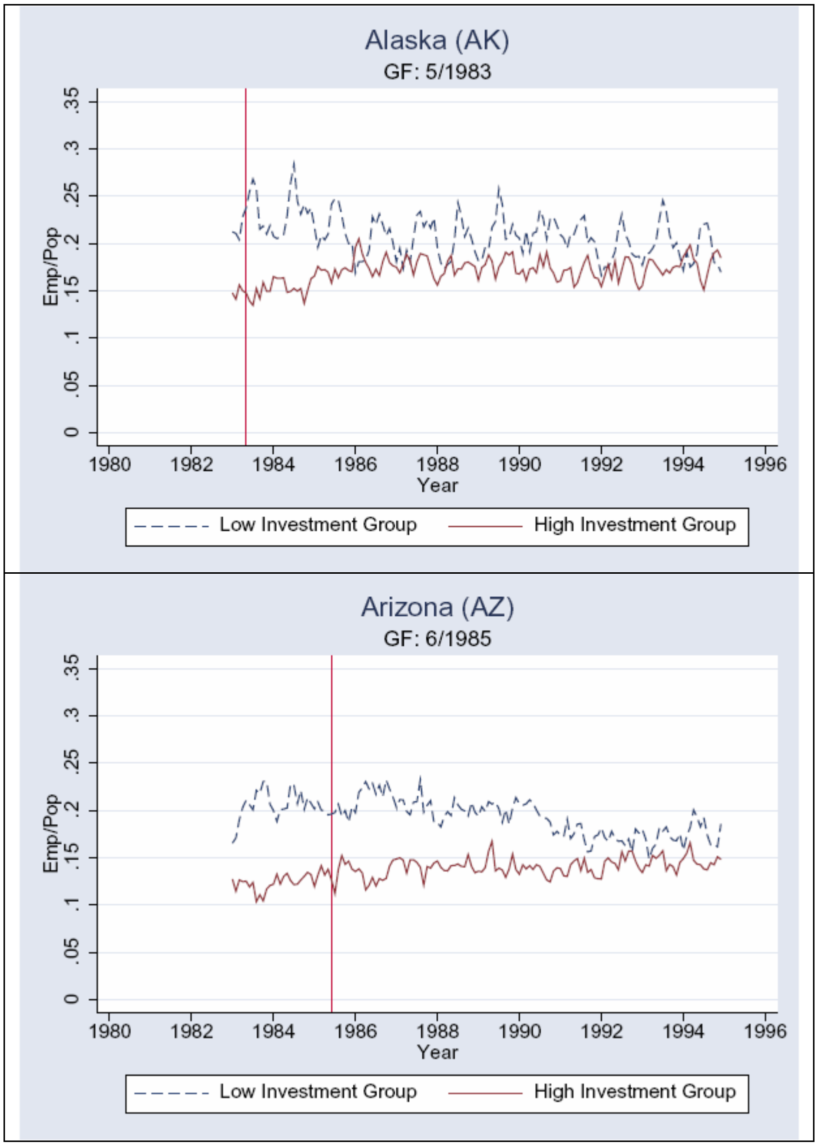
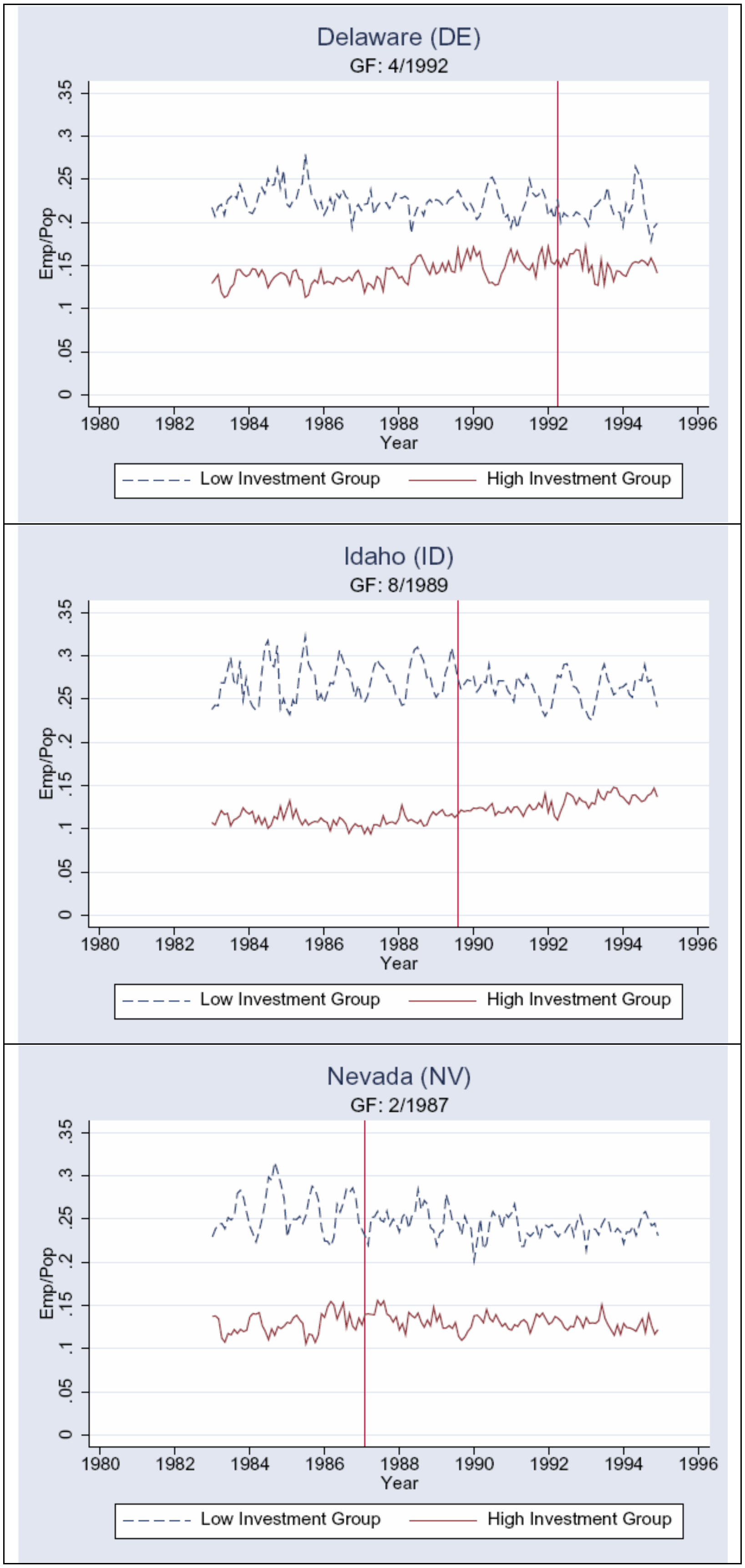
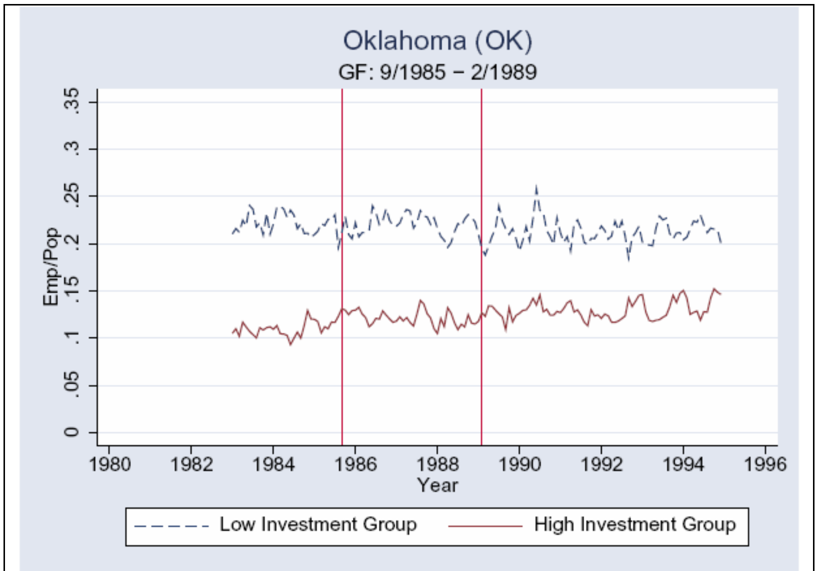
Good Faith Exception February 1983	Good Faith Exception December 1994
	

Figure 3: Employment per Population for States Adopting Good Faith Exception during 1983-1994
High-Investment Group VS Low-Investment Group (any Kind of Training Criterion)





Delaware (DE)
GF: 4/1992
Emp/Pop
0
.05
.1
.15
.2
.25
.3
.35
1980
1982
1984
1986
1988
1990
1992
1994
1996
Year
Low Investment Group
High Investment Group
Idaho (ID)
GF: 8/1989
Emp/Pop
0
.05
.1
.15
.2
.25
.3
.35
1980
1982
1984
1986
1988
1990
1992
1994
1996
Year
Low Investment Group
High Investment Group
Nevada (NV)
GF: 2/1987
Emp/Pop
0
.05
.1
.15
.2
.25
.3
.35
1980
1982
1984
1986
1988
1990
1992
1994
1996
Year
Low Investment Group
High Investment Group


Oklahoma (OK)
GF: 9/1985 – 2/1989
Emp/Pop
0
.05
.1
.15
.2
.25
.3
.35
1980
1982
1984
1986
1988
1990
1992
1994
1996
Year
Low Investment Group
High Investment Group

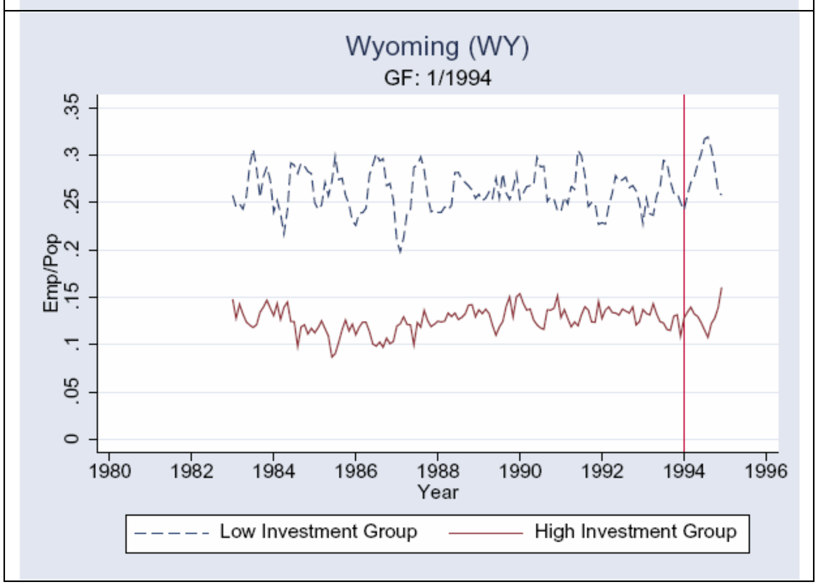

Wyoming (WY)
GF: 1/1994
Emp/Pop
0
.05
.1
.15
.2
.25
.3
.35
1980
1982
1984
1986
1988
1990
1992
1994
1996
Year
Low Investment Group
High Investment Group

Figure 4A: States that contain "Highly populated area"
SMSA with population 1M+ (1983-1984)

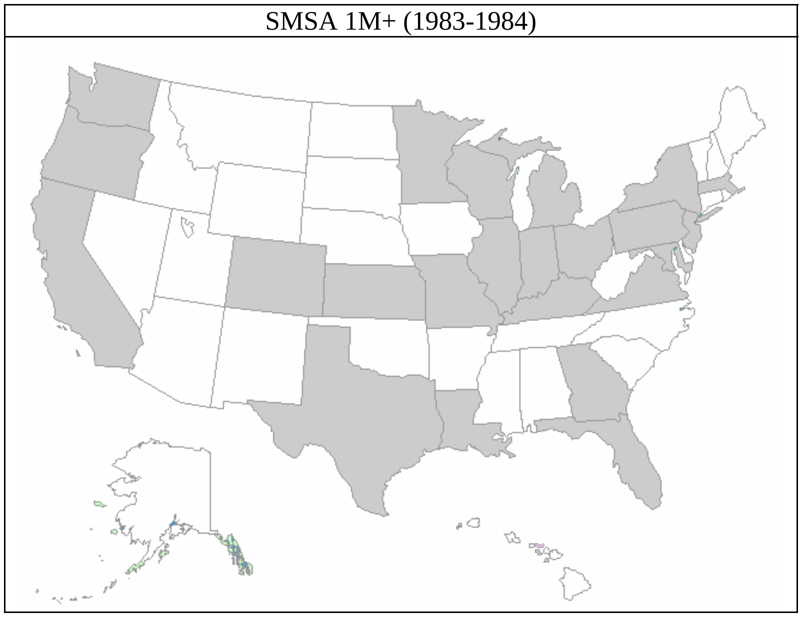


Figure 4B: States that contain "Highly populated area"
MSA with population 1M+ (1985-1994)

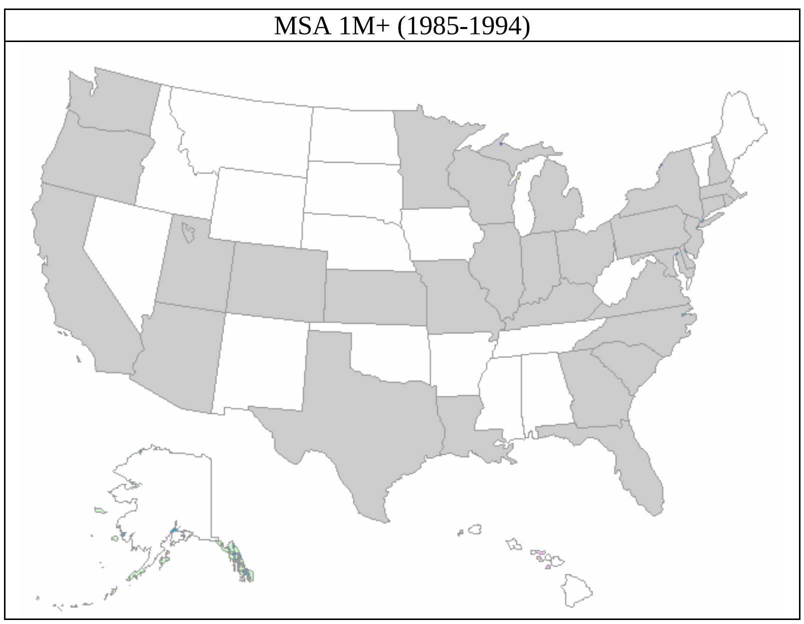


Table 1: Adoption Dates

State		Implied Contract	Public Policy	Good Faith	Remarks
ALABAMA	AL	7/1987			
ALASKA	AK	5/1983	2/1986	5/1983	
ARIZONA	AZ	6/1983	6/1985	6/1985	
ARKANSAS	AR	6/1984	3/1980		
CALIFORNIA	CA	3/1972	9/1959	10/1980	
COLORADO	CO	10/1983	9/1985		
CONNECTICUT	CT	10/1985	1/1980	6/1980	
DELAWARE	DE		3/1992	4/1992	
FLORIDA	FL				
GEORGIA	GA				
HAWAII	HI	8/1986	10/1982		
IDAHO	ID	4/1977	4/1977	8/1989	
ILLINOIS	IL	12/1974	12/1978		
INDIANA	IN	8/1987	5/1973		
IOWA	IA	11/1987	7/1985		
KANSAS	KS	8/1984	6/1981		
KENTUCKY	KY	8/1983	11/1983		
LOUISIANA	LA			1/1998	
MAINE	ME	11/1977			
MARYLAND	MD	1/1985	7/1981		
MASSACHUSETTS	MA	5/1988	5/1980	7/1977	
MICHIGAN	MI	6/1980	6/1976		
MINNESOTA	MN	4/1983	11/1986		
MISSISSIPPI	MS	6/1992	7/1987		
MISSOURI	MO	1/1983	11/1985		End Implied Contract in 2/1988
MONTANA	MT	6/1987	1/1980	1/1982	
NEBRASKA	NE	11/1983	11/1987		
NEVADA	NV	8/1983	1/1984	2/1987	
NEW HAMPSHIRE	NH	8/1988	2/1974	2/1974	End Good Faith in 5/1980
NEW JERSEY	NJ	5/1985	7/1980		
NEW MEXICO	NM	2/1980	7/1983		
NEW YORK	NY	11/1982			
NORTH CAROLINA	NC		5/1985		
NORTH DAKOTA	ND	2/1984	11/1987		
OHIO	OH	4/1982	3/1990		
OKLAHOMA	OK	12/1976	2/1989	5/1985	End Good Faith in 2/1989
OREGON	OR	3/1978	6/1975		
PENNSYLVANIA	PA		3/1974		
RHODE ISLAND	RI				
SOUTH CAROLINA	SC	6/1987	11/1985		
SOUTH DAKOTA	SD	4/1983	12/1988		
TENNESSEE	TN	11/1981	8/1984		
TEXAS	TX	4/1985	6/1984		
UTAH	UT	5/1986	3/1989		
VERMONT	VT	8/1985	9/1986		
VIRGINIA	VA	9/1983	6/1985		
WASHINGTON	WA	8/1977	7/1984		
WEST VIRGINIA	WV	4/1986	7/1978		
WISCONSIN	WI	6/1985	1/1980		
WYOMING	WY	8/1985	7/1989	1/1994	

Source: Summarized from Autor, Donohue, and Schwab (2006)'s Legal Appendix

Table 2A: Fraction of Workers Received any Kind of Training after Obtaining Current Job

Occupation Code	Occupation	Fraction of workers received any kind of training after obtaining current job	Group
27	Private Household Service Occupations	0.0544938	Low
38	Motor Vehicle Operators	0.1389347	
31	Cleaning and Building Service Occupations	0.1481309	
41	Freight, Stock and Material Handlers	0.1481502	
45	Forestry and Fishing Occupations	0.1483199	
44	Farm Workers and Related Occupations	0.1560583	
29	Food Service Occupations	0.1584234	
42	Other Handlers, Equipment Cleaners, and Laborers	0.1727826	
40	Construction Laborers	0.1735819	
43	Farm Operators and Managers	0.2040806	
36	Machine Operators and Tenders, Except Precision	0.2259195	
19	Sales Workers, Retail and Personal Services	0.2275931	
39	Other Transportation Occupations and Material Moving	0.2478085	
37	Fabricators, Assemblers, Inspectors, and Samplers	0.2557604	
34	Construction Trades	0.2847712	
25	Mail and Message Distributing	0.3050183	Medium
23	Secretaries, Stenographers, and Typists	0.307571	
24	Financial Records, Processing Occupations	0.311928	
16	Supervisors and Proprietors, Sales Occupations	0.3471562	
32	Personal Service Occupations	0.3598349	
35	Other Precision Production Occupations	0.375325	
26	Other Administrative Support Occupations, Including Clerical	0.3822806	
18	Sales Representatives Commodities, Except Retail	0.4198851	
30	Health Service Occupations	0.4331955	
2	Other Executive, Administrators, and Managers	0.4601972	
33	Mechanics and Repairers	0.4694868	
22	Computer Equipment Operators	0.4787066	
21	Supervisors-Administrative Support	0.5052693	
14	Engineering and Science Technicians	0.5078194	
9	Teachers, College and University	0.5151968	
20	Sales Related Occupations	0.5169604	High
13	Health Technologists and Technicians	0.5297871	
3	Management Related Occupations	0.5339963	
12	Other Professional Specialty Occupations	0.542066	
11	Lawyers and Judges	0.5813953	
15	Technicians, Except Health Engineering, and Science	0.5824444	
4	Engineers	0.5877689	
17	Sales Representatives, Finance, and Business Service	0.6136144	
6	Natural Scientists	0.6139696	
28	Protective Service Occupations	0.6315429	
5	Mathematical and Computer Scientists	0.6743543	
8	Health Assessment and Treating Occupations	0.6800746	
1	Administrators and Officials, Public Administration	0.716915	
7	Health Diagnosing Occupations	0.7292728	
10	Teachers, Except College and University	0.7653595	

Table 2B: Fraction of Workers Received (Employer Paid) School Training after Obtaining Current Job

Occupation Code	Occupation	Fraction of workers received (employer paid) school training after obtaining current job	Group
25	Mail and Message Distributing	0	Low
27	Private Household Service Occupations	0	
41	Freight, Stock and Material Handlers	0	
40	Construction Laborers	0.0063221	
38	Motor Vehicle Operators	0.0068844	
42	Other Handlers, Equipment Cleaners, and Laborers	0.0075406	
31	Cleaning and Building Service Occupations	0.00789	
36	Machine Operators and Tenders, Except Precision	0.0089007	
44	Farm Workers and Related Occupations	0.0096675	
19	Sales Workers, Retail and Personal Services	0.0098459	
39	Other Transportation Occupations and Material Moving	0.0149699	
29	Food Service Occupations	0.0171672	
45	Forestry and Fishing Occupations	0.0254529	
43	Farm Operators and Managers	0.026601	
37	Fabricators, Assemblers, Inspectors, and Samplers	0.0281746	
32	Personal Service Occupations	0.0309196	Medium
30	Health Service Occupations	0.034261	
34	Construction Trades	0.0361907	
16	Supervisors and Proprietors, Sales Occupations	0.0378588	
33	Mechanics and Repairers	0.0392179	
26	Other Administrative Support Occupations, Including Clerical	0.0428515	
23	Secretaries, Stenographers, and Typists	0.0506456	
35	Other Precision Production Occupations	0.0512298	
18	Sales Representatives Commodities, Except Retail	0.0559219	
24	Financial Records, Processing Occupations	0.0560466	
22	Computer Equipment Operators	0.0569106	
11	Lawyers and Judges	0.0628524	
17	Sales Representatives, Finance, and Business Service	0.0741983	
13	Health Technologists and Technicians	0.0762671	
8	Health Assessment and Treating Occupations	0.0820884	
20	Sales Related Occupations	0.083898	High
2	Other Executive, Administrators, and Managers	0.0872607	
21	Supervisors-Administrative Support	0.0927648	
12	Other Professional Specialty Occupations	0.0983718	
14	Engineering and Science Technicians	0.1035796	
3	Management Related Occupations	0.1057448	
1	Administrators and Officials, Public Administration	0.116992	
15	Technicians, Except Health Engineering, and Science	0.1187169	
9	Teachers, College and University	0.1224448	
7	Health Diagnosing Occupations	0.128199	
10	Teachers, Except College and University	0.1318544	
28	Protective Service Occupations	0.1384961	
4	Engineers	0.149489	
5	Mathematical and Computer Scientists	0.1637195	
6	Natural Scientists	0.1961244	

Table 2C: Fraction of Workers Received Formal Company Training after Obtaining Current Job

Occupation Code	Occupation	Fraction of workers received formal company training after obtaining current job	Group
43	Farm Operators and Managers	0.0175515	Low
29	Food Service Occupations	0.0220365	
27	Private Household Service Occupations	0.0226557	
44	Farm Workers and Related Occupations	0.0227975	
41	Freight, Stock and Material Handlers	0.0260338	
31	Cleaning and Building Service Occupations	0.0296611	
40	Construction Laborers	0.0303548	
42	Other Handlers, Equipment Cleaners, and Laborers	0.0337012	
36	Machine Operators and Tenders, Except Precision	0.0362584	
9	Teachers, College and University	0.0415534	
38	Motor Vehicle Operators	0.0458973	
45	Forestry and Fishing Occupations	0.0475126	
37	Fabricators, Assemblers, Inspectors, and Samplers	0.0548318	
19	Sales Workers, Retail and Personal Services	0.0653655	
24	Financial Records, Processing Occupations	0.070279	
39	Other Transportation Occupations and Material Moving	0.075374	Medium
34	Construction Trades	0.0762882	
7	Health Diagnosing Occupations	0.0822099	
23	Secretaries, Stenographers, and Typists	0.0826247	
25	Mail and Message Distributing	0.0828437	
10	Teachers, Except College and University	0.0961728	
32	Personal Service Occupations	0.1006098	
11	Lawyers and Judges	0.106687	
30	Health Service Occupations	0.1215534	
12	Other Professional Specialty Occupations	0.1334349	
26	Other Administrative Support Occupations, Including Clerical	0.1346527	
35	Other Precision Production Occupations	0.1388943	
16	Supervisors and Proprietors, Sales Occupations	0.1399342	
13	Health Technologists and Technicians	0.1562996	
2	Other Executive, Administrators, and Managers	0.1639372	
14	Engineering and Science Technicians	0.1878971	High
22	Computer Equipment Operators	0.1916446	
3	Management Related Occupations	0.2095282	
18	Sales Representatives Commodities, Except Retail	0.2211782	
20	Sales Related Occupations	0.2230621	
21	Supervisors-Administrative Support	0.2420617	
33	Mechanics and Repairers	0.2428236	
15	Technicians, Except Health Engineering, and Science	0.2572868	
8	Health Assessment and Treating Occupations	0.2588073	
6	Natural Scientists	0.2752914	
4	Engineers	0.2920008	
17	Sales Representatives, Finance, and Business Service	0.2950807	
28	Protective Service Occupations	0.3279191	
1	Administrators and Officials, Public Administration	0.3502091	
5	Mathematical and Computer Scientists	0.3817046	

Table 2D: Fraction of Workers Received Informal on-the-job Training after Obtaining Current Job

Occupation Code	Occupation	Fraction of workers received informal on-the-job training after obtaining current job	Group
20	Sales Related Occupations	0	Low
27	Private Household Service Occupations	0.0336552	
43	Farm Operators and Managers	0.054813	
45	Forestry and Fishing Occupations	0.0628462	
38	Motor Vehicle Operators	0.0734377	
32	Personal Service Occupations	0.0769121	
9	Teachers, College and University	0.0786915	
7	Health Diagnosing Occupations	0.0829758	
31	Cleaning and Building Service Occupations	0.0922231	
44	Farm Workers and Related Occupations	0.0937638	
10	Teachers, Except College and University	0.0949497	
29	Food Service Occupations	0.0999658	
11	Lawyers and Judges	0.1074059	
41	Freight, Stock and Material Handlers	0.1123306	
23	Secretaries, Stenographers, and Typists	0.1165614	
42	Other Handlers, Equipment Cleaners, and Laborers	0.1187727	Medium
40	Construction Laborers	0.1232443	
34	Construction Trades	0.1340891	
24	Financial Records, Processing Occupations	0.1342847	
19	Sales Workers, Retail and Personal Services	0.1357762	
16	Supervisors and Proprietors, Sales Occupations	0.1369977	
2	Other Executive, Administrators, and Managers	0.1494641	
39	Other Transportation Occupations and Material Moving	0.1505784	
6	Natural Scientists	0.1520941	
37	Fabricators, Assemblers, Inspectors, and Samplers	0.1591837	
36	Machine Operators and Tenders, Except Precision	0.1677804	
21	Supervisors-Administrative Support	0.1708288	
12	Other Professional Specialty Occupations	0.1747022	
3	Management Related Occupations	0.1767491	
18	Sales Representatives Commodities, Except Retail	0.1795304	
35	Other Precision Production Occupations	0.1818477	High
33	Mechanics and Repairers	0.1840206	
4	Engineers	0.1893195	
14	Engineering and Science Technicians	0.1927129	
8	Health Assessment and Treating Occupations	0.1975016	
26	Other Administrative Support Occupations, Including Clerical	0.1978101	
13	Health Technologists and Technicians	0.1988621	
17	Sales Representatives, Finance, and Business Service	0.2034024	
25	Mail and Message Distributing	0.2188927	
30	Health Service Occupations	0.2285811	
15	Technicians, Except Health Engineering, and Science	0.2380981	
28	Protective Service Occupations	0.2415931	
5	Mathematical and Computer Scientists	0.2467641	
1	Administrators and Officials, Public Administration	0.2600389	
22	Computer Equipment Operators	0.2660764	

Table 3: Average Tenure by Occupation Group (Low, Medium, High)
Using January 1987 Job Tenure Supplement Data
Occupation Groups Categorized by Any Kind of Training Criterion

State	Abbre.	Average Tenure (Month)		
		Low Investment	**Medium Investment**	**High Investment**
ALABAMA	AL	71.85928	95.93007	94.60897
ALASKA	AK	44.91544	61.06683	69.67273
ARIZONA	AZ	43.55752	66.84146	71.01797
ARKANSAS	AR	76.32993	95.16666	85.32624
CALIFORNIA	CA	51.38254	77.85999	89.47134
COLORADO	CO	45.5561	83.60738	76.09278
CONNECTICUT	CT	75.57391	94.46726	87.44086
DELAWARE	DE	63.52968	98.98154	99.73793
FLORIDA	FL	48.38214	72.60717	76.60201
GEORGIA	GA	64.84536	83.03503	82.71605
HAWAII	HI	67.58373	91.41522	104.1677
IDAHO	ID	88.90432	87.10069	93.8
ILLINOIS	IL	81.57316	94.02778	91.76667
INDIANA	IN	90.11579	112.8485	103.2174
IOWA	IA	105.0052	96.2381	105.2611
KANSAS	KS	85.12337	94.68671	90.28492
KENTUCKY	KY	81.75658	115.1985	83.51145
LOUISIANA	LA	69.77941	96.36864	93.38519
MAINE	ME	77.52049	82.2085	87.78689
MARYLAND	MD	73.25267	88.82998	104.4291
MASSACHUSETTS	MA	64.27689	89.71149	88.22314
MICHIGAN	MI	83.13192	98.72752	95.36842
MINNESOTA	MN	79.97472	102.299	91.70139
MISSISSIPPI	MS	75	99.07266	99.4875
MISSOURI	MO	80.25475	81.79856	90.56221
MONTANA	MT	111.2143	80.22005	93.63461
NEBRASKA	NE	109.5028	96.87936	100.241
NEVADA	NV	46.48052	66.78351	74.128
NEW HAMPSHIRE	NH	49.63913	79.24915	81.24219
NEW JERSEY	NJ	74.21204	94.26456	93.82388
NEW MEXICO	NM	67.82231	76.34193	74.56021
NEW YORK	NY	76.90549	96.89936	107.9772
NORTH CAROLINA	NC	75.54038	91.58715	92.07049
NORTH DAKOTA	ND	114.9864	92.72853	90.99445
OHIO	OH	82.75395	101.0155	104.5486
OKLAHOMA	OK	79.29964	90.80264	86.96053
OREGON	OR	64.87295	79.7874	84.93877
PENNSYLVANIA	PA	85.17342	105.1751	108.8861
RHODE ISLAND	RI	78.85268	93.75207	93.60545
SOUTH CAROLINA	SC	81.83146	113.0135	96.74097
SOUTH DAKOTA	SD	114.8813	91.80214	101.9538
TENNESSEE	TN	75.65517	97.04575	98.92
TEXAS	TX	58.15458	70.83622	76.47369
UTAH	UT	50.48235	77.45705	100.858
VERMONT	VT	72.72161	81.65019	93.92958
VIRGINIA	VA	79.27005	84.22811	91.14634
WASHINGTON	WA	56.30213	87.95752	90.33334
WEST VIRGINIA	WV	95.05627	116.2244	113.5505
WISCONSIN	WI	91.50503	103.0179	111.5723
WYOMING	WY	74.40816	74.53036	101.3211

Table 4A: **Good Faith** Exception (**All Areas**) [Dep Var: **LN(emp/pop)** by occupation group Low, Medium, High]
Weighted Least Square [Weight = (sqrt of) # of obs that belong to each occupation group]
Controls are at the occupation group level; Standard errors are clustered by state

	Any Training		School Training		Formal Training		Informal Training	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Adopt(GF)	0.04769***	0.03084*	0.01602	0.00517	0.04180***	0.03442**	0.00851	0.01909
	(0.01818)	(0.01586)	(0.01507)	(0.01711)	(0.01600)	(0.01560)	(0.02092)	(0.02094)
Adopt(GF)xLow	-0.15323***	-0.10579**	-0.13245***	-0.10088**	-0.14348***	-0.10509**	-0.05675	-0.06768
	(0.05130)	(0.04581)	(0.05027)	(0.05052)	(0.04965)	(0.04664)	(0.06690)	(0.06589)
Adopt(GF)xHigh	0.07932**	0.08361**	0.13019***	0.13958***	0.06270***	0.03088	0.03862*	0.02576
	(0.03571)	(0.03967)	(0.02857)	(0.02337)	(0.02187)	(0.02258)	(0.02188)	(0.02343)
Low	-0.03842	0.08549	-0.12523***	0.01009	-0.19032***	0.11703*	-0.36121***	-0.32638***
	(0.02922)	(0.07356)	(0.02837)	(0.06752)	(0.02981)	(0.06866)	(0.02926)	(0.06348)
High	-0.69975***	-1.24093***	-0.49909***	-0.95214***	-0.81565***	-0.91238***	-0.41121***	-0.29929***
	(0.01852)	(0.10851)	(0.01978)	(0.10670)	(0.01285)	(0.05256)	(0.01661)	(0.03335)
LowXt	-0.00098***	-0.00082***	-0.00071***	-0.00083***	-0.00129***	-0.00125***	-0.00057***	-0.00081***
	(0.00013)	(0.00021)	(0.00012)	(0.00021)	(0.00013)	(0.00021)	(0.00012)	(0.00017)
HighXt	0.00086***	0.00099***	0.00123***	0.00133***	-0.00013**	-0.00036***	0.00040***	0.00055***
	(0.00009)	(0.00016)	(0.00009)	(0.00019)	(0.00006)	(0.00010)	(0.00009)	(0.00010)
%male		0.02499		0.13540		-0.02577		0.69998***
		(0.15309)		(0.20751)		(0.21426)		(0.27000)
%black		0.31604		0.10249		0.06945		-0.29700
		(0.24825)		(0.27232)		(0.25660)		(0.24633)
%age18-35		-0.55691**		-0.37590		-0.48610		-0.58359**
		(0.28140)		(0.31165)		(0.30011)		(0.29203)
%age36-55		-0.50272*		-0.23262		-0.45837*		-0.86699***
		(0.29281)		(0.31959)		(0.27585)		(0.28863)
%married		-0.22578		-0.06661		-0.13742		0.01101
		(0.22267)		(0.18963)		(0.15323)		(0.11247)
%union		-0.66118		-0.91275		-0.56566		-0.13489
		(0.52568)		(0.61369)		(0.45116)		(0.31220)
%high school education		0.25193		0.55336**		0.50149**		-0.53577***
		(0.24078)		(0.26346)		(0.25245)		(0.16498)
%some college education		-0.19957		0.01116		0.20401		-0.89671***
		(0.32873)		(0.33022)		(0.30201)		(0.28533)
%college education and higher		1.60344***		1.52264***		1.90197***		-0.64401**
		(0.36798)		(0.41000)		(0.36233)		(0.28887)
Constant	-1.37015***	-1.11489***	-1.40226***	-1.63952***	-1.26966***	-1.49169***	-1.34302***	-0.59853**
	(0.00944)	(0.38475)	(0.00723)	(0.40869)	(0.01056)	(0.31164)	(0.00840)	(0.26393)
Observations	21450	21450	21450	21450	21450	21450	21450	21450
R-squared	0.84	0.87	0.72	0.75	0.90	0.92	0.83	0.85
T test: Adopt+AdoptxLow=0	**-0.10554**	**-0.07495**	**-0.11642**	**-0.09570**	**-0.10168**	**-0.07068**	-0.04824	-0.04859
T-stat_1	**-2.85133**	**-2.06818**	**-2.96215**	**-2.37504**	**-2.81167**	**-1.93996**	-0.99206	-1.00996
test: Adopt+AdoptxHigh=0	**0.12701**	**0.11445**	**0.14621**	**0.14476**	**0.10450**	**0.06530**	0.04713	0.04485
T-stat_2	**2.85279**	**2.58367**	**3.95955**	**4.60314**	**3.03862**	**1.97239**	1.57542	1.49132
F test: Adopt=AdoptxLow=AdoptxHigh=0	3.14568	2.47329	7.68504	14.31559	3.09612	1.95092	1.10577	0.89364
Prob > F	0.02403	0.05968	0.00004	0.00000	0.02571	0.11903	0.34526	0.44350

Robust standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4B: **Good Faith** Exception (**All Areas**) [Dep Var: **LN(avg wage)** by occupation group Low, Medium, High]

Weighted Least Square [Weight = (sqrt of) # of obs that belong to each occupation group that have valid wage information]

Controls are at the occupation group level; Standard errors are clustered by state

	Any Training		School Training		Formal Training		Informal Training	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Adopt(GF)	0.00968	0.00937	0.01786*	0.01584	0.01866*	0.01660	0.01041	0.01060
	(0.00965)	(0.01144)	(0.00931)	(0.01048)	(0.01003)	(0.01216)	(0.00910)	(0.01139)
Adopt(GF)xLow	-0.01194	-0.00748	-0.03330	-0.02566**	-0.02969	-0.01881	-0.00141	-0.00049
	(0.02121)	(0.01230)	(0.02231)	(0.01272)	(0.02085)	(0.01508)	(0.01107)	(0.00891)
Adopt(GF)xHigh	0.01139	0.00618	-0.00539	-0.00029	-0.00503	-0.01181**	-0.00561	-0.01032*
	(0.01490)	(0.01316)	(0.01326)	(0.01347)	(0.00632)	(0.00548)	(0.01073)	(0.00617)
Low	-0.29351***	-0.18735***	-0.29926***	-0.19555***	-0.36524***	-0.19511***	-0.30303***	-0.20981***
	(0.00866)	(0.01025)	(0.00824)	(0.00822)	(0.00805)	(0.00840)	(0.00827)	(0.00982)
High	0.19694***	-0.00314	0.29347***	0.06162***	0.18847***	0.09605***	0.03057***	0.02129***
	(0.00702)	(0.01099)	(0.00836)	(0.00983)	(0.00467)	(0.00729)	(0.00717)	(0.00434)
LowXt	-0.00037***	-0.00040***	-0.00025***	-0.00028***	-0.00025***	-0.00024***	0.00054***	0.00044***
	(0.00006)	(0.00006)	(0.00006)	(0.00005)	(0.00006)	(0.00005)	(0.00004)	(0.00004)
HighXt	0.00046***	0.00061***	0.00020***	0.00040***	0.00016***	0.00015***	0.00005	0.00006*
	(0.00004)	(0.00003)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00005)	(0.00004)
%male		0.32344***		0.28641***		0.21983***		0.25069***
		(0.01789)		(0.02097)		(0.01986)		(0.02017)
%black		-0.11003***		-0.09033***		-0.06340**		-0.10110**
		(0.02898)		(0.03392)		(0.03096)		(0.04584)
%age18-35		-0.15793***		-0.16113***		-0.16947***		-0.11930***
		(0.03067)		(0.03345)		(0.02737)		(0.02180)
%age36-55		0.04615*		0.02913		0.05504**		0.09975***
		(0.02709)		(0.02944)		(0.02256)		(0.02647)
%married		0.12987***		0.13795***		0.13578***		0.17806***
		(0.02095)		(0.01962)		(0.01800)		(0.01297)
%union		0.28657***		0.27704***		0.29199***		0.27403***
		(0.04233)		(0.04887)		(0.04022)		(0.03375)
%high school education		0.33703***		0.31594***		0.26953***		0.21695***
		(0.05129)		(0.04430)		(0.03369)		(0.02242)
%some college education		0.39264***		0.38979***		0.34450***		0.37805***
		(0.05101)		(0.04696)		(0.03684)		(0.03271)
%college education and higher		0.68443***		0.67174***		0.69451***		0.80976***
		(0.05073)		(0.04268)		(0.03883)		(0.02965)
Constant	2.02341***	1.41997***	1.98276***	1.43318***	2.04735***	1.48917***	2.01185***	1.39934***
	(0.00366)	(0.03452)	(0.00290)	(0.03221)	(0.00335)	(0.03218)	(0.00310)	(0.03744)
Observations	21450	21450	21450	21450	21450	21450	21450	21450
R-squared	0.92	0.93	0.93	0.94	0.93	0.94	0.84	0.87
T test: Adopt+AdoptxLow=0	-0.00226	0.00189	-0.01544	-0.00982	-0.01103	-0.00221	0.00900	0.01011
T-stat_1	-0.12395	0.12048	-0.85795	-0.65347	-0.70923	-0.15888	0.81131	0.80381
test: Adopt+AdoptxHigh=0	0.02107	0.01555	0.01247	0.01555	0.01363	0.00479	0.00480	0.00028
T-stat_2	1.04605	0.83118	0.75038	0.88251	1.16141	0.40313	0.43447	0.02369
F test: Adopt=AdoptxLow=AdoptxHigh=0	0.45314	0.31001	1.60183	4.65545	1.42083	1.77198	0.48278	1.05443
Prob > F	0.71508	0.81817	0.18664	0.00296	0.23451	0.15011	0.69425	0.36715

Robust standard errors in parentheses

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

Table 5A: **Implied Contract** Exception (**All Areas**) [Dep Var: **LN(emp/pop)** by occupation group Low, Medium, High]

Weighted Least Square [Weight = (sqrt of) # of obs that belong to each occupation group]

Controls are at the occupation group level; Standard errors are clustered by state

	Any Training		School Training		Formal Training		Informal Training	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Adopt(IC)	-0.00295	-0.01155	-0.02634*	-0.03566***	-0.00713	-0.01206	-0.04058**	-0.03035*
	(0.01400)	(0.01088)	(0.01379)	(0.01131)	(0.01540)	(0.01512)	(0.01741)	(0.01612)
Adopt(IC)xLow	-0.05559	-0.02754	-0.01871	-0.00141	-0.03244	-0.00973	0.05720	0.04171
	(0.04372)	(0.03190)	(0.04490)	(0.03293)	(0.04674)	(0.03727)	(0.03802)	(0.03193)
Adopt(IC)xHigh	0.05300**	0.03634	0.07893***	0.07857***	0.02912*	0.00945	0.03573	0.02907
	(0.02442)	(0.02661)	(0.02481)	(0.02751)	(0.01501)	(0.01141)	(0.02664)	(0.02707)
Low	-0.03211	0.10258*	-0.13413***	0.02116	-0.19454***	0.14090**	-0.39951***	-0.36558***
	(0.02876)	(0.05765)	(0.03196)	(0.06432)	(0.03181)	(0.06510)	(0.02845)	(0.06483)
High	-0.71351***	-1.25428***	-0.51723***	-0.97646***	-0.81982***	-0.92097***	-0.42324***	-0.31365***
	(0.01936)	(0.10993)	(0.01876)	(0.13135)	(0.01265)	(0.04980)	(0.02266)	(0.03923)
LowXt	-0.00089***	-0.00084***	-0.00071***	-0.00097***	-0.00126***	-0.00128***	-0.00075***	-0.00091***
	(0.00020)	(0.00024)	(0.00019)	(0.00024)	(0.00019)	(0.00026)	(0.00019)	(0.00022)
HighXt	0.00074***	0.00091***	0.00106***	0.00121***	-0.00019**	-0.00037***	0.00031***	0.00047***
	(0.00010)	(0.00018)	(0.00011)	(0.00020)	(0.00008)	(0.00010)	(0.00011)	(0.00012)
%male		0.07756		0.20724		0.00194		0.69256**
		(0.17304)		(0.21601)		(0.20459)		(0.27112)
%black		0.50558**		0.36715		0.25186		-0.11713
		(0.22369)		(0.26204)		(0.21665)		(0.21915)
%age18-35		-0.75000***		-0.59458*		-0.63548**		-0.70980**
		(0.28121)		(0.34227)		(0.28446)		(0.34296)
%age36-55		-0.58514**		-0.31703		-0.52633**		-0.97427***
		(0.25890)		(0.30099)		(0.23068)		(0.31196)
%married		-0.23657		-0.06552		-0.18605		-0.01105
		(0.19183)		(0.17629)		(0.13025)		(0.11161)
%union		-0.47778		-0.78629		-0.46207		-0.23430
		(0.52346)		(0.63578)		(0.46656)		(0.29016)
%high school education		0.46294**		0.87824***		0.69749***		-0.47278**
		(0.20983)		(0.25605)		(0.18923)		(0.19643)
%some college education		-0.09640		0.20548		0.36651		-0.80562***
		(0.28051)		(0.28136)		(0.23106)		(0.30235)
%college education and higher		1.78126***		1.73500***		2.14787***		-0.46920
		(0.32645)		(0.40341)		(0.29534)		(0.32843)
Constant	-1.35466***	-1.16261***	-1.37642***	-1.75603***	-1.25271***	-1.54813***	-1.30876***	-0.53079**
	(0.01258)	(0.37033)	(0.01366)	(0.41851)	(0.01370)	(0.30443)	(0.01585)	(0.24281)
Observations	21450	21450	21450	21450	21450	21450	21450	21450
R-squared	0.83	0.86	0.69	0.72	0.90	0.92	0.82	0.84
T test: Adopt+AdoptxLow=0	**-0.05854**	-0.03909	-0.04505	-0.03707	-0.03957	-0.02179	0.01662	0.01136
T-stat_1	**-1.78902**	-1.53161	-1.27482	-1.30908	-1.17721	-0.84358	0.61996	0.52893
test: Adopt+AdoptxHigh=0	0.05005	0.02480	**0.05259**	0.04291	0.02200	-0.00261	-0.00485	-0.00128
T-stat_2	1.45123	0.78984	**1.66358**	1.39747	0.80703	-0.13679	-0.26089	-0.07596
F test: Adopt=AdoptxLow=AdoptxHigh=0	2.94081	2.05230	6.27228	7.29161	3.43281	1.25496	2.12882	1.56166
Prob > F	0.03177	0.10426	0.00030	0.00007	0.01621	0.28803	0.09428	0.19641

Robust standard errors in parentheses

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

Table 5B: **Implied Contract** Exception (**All Areas**) [Dep Var: **LN(avg wage)** by occupation group Low, Medium, High]

Weighted Least Square [Weight = (sqrt of) # of obs that belong to each occupation group that have valid wage information]

Controls are at the occupation group level; Standard errors are clustered by state

	Any Training		School Training		Formal Training		Informal Training	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Adopt(IC)	-0.00064	0.00864*	0.00661	0.00907	0.01032*	0.01293**	0.02488***	0.01846***
	(0.00700)	(0.00484)	(0.00747)	(0.00555)	(0.00531)	(0.00537)	(0.00678)	(0.00472)
Adopt(IC)xLow	0.01576	-0.00838	0.00367	-0.01302	-0.00554	-0.01545*	-0.03079***	-0.02422***
	(0.01359)	(0.00673)	(0.01437)	(0.00880)	(0.01143)	(0.00915)	(0.01185)	(0.00725)
Adopt(IC)xHigh	0.00948	-0.00281	-0.00098	0.00279	-0.00566	-0.00993*	-0.02549**	-0.01792***
	(0.00909)	(0.00730)	(0.00848)	(0.00680)	(0.00585)	(0.00549)	(0.01046)	(0.00501)
Low	-0.30343***	-0.18393***	-0.30611***	-0.19029***	-0.36687***	-0.18819***	-0.28723***	-0.19772***
	(0.00986)	(0.01080)	(0.01011)	(0.00988)	(0.00748)	(0.00920)	(0.00867)	(0.00876)
High	0.19396***	-0.00126	0.29330***	0.05661***	0.19071***	0.09673***	0.04296***	0.02968***
	(0.00610)	(0.01211)	(0.00702)	(0.01059)	(0.00343)	(0.00709)	(0.00728)	(0.00421)
LowXt	-0.00041***	-0.00038***	-0.00027***	-0.00025***	-0.00025***	-0.00021***	0.00062***	0.00051***
	(0.00005)	(0.00006)	(0.00005)	(0.00005)	(0.00005)	(0.00006)	(0.00006)	(0.00005)
HighXt	0.00044***	0.00062***	0.00020***	0.00040***	0.00018***	0.00017***	0.00011***	0.00011***
	(0.00005)	(0.00004)	(0.00005)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)
%male		0.32792***		0.29299***		0.23004***		0.24827***
		(0.01703)		(0.01842)		(0.01786)		(0.02057)
%black		-0.11062***		-0.08480**		-0.06581**		-0.11911***
		(0.03245)		(0.03738)		(0.03083)		(0.03665)
%age18-35		-0.16236***		-0.17045***		-0.17128***		-0.11423***
		(0.03829)		(0.04758)		(0.03212)		(0.02042)
%age36-55		0.04421		0.02361		0.05362**		0.10371***
		(0.02891)		(0.03471)		(0.02513)		(0.02589)
%married		0.12845***		0.13495***		0.13334***		0.17884***
		(0.02193)		(0.02235)		(0.02028)		(0.01169)
%union		0.29281***		0.28504***		0.29400***		0.27558***
		(0.04379)		(0.05090)		(0.04225)		(0.02839)
%high school education		0.34336***		0.33340***		0.27876***		0.20675***
		(0.05501)		(0.05737)		(0.03973)		(0.02262)
%some college education		0.39568***		0.40676***		0.35511***		0.36491***
		(0.05104)		(0.05777)		(0.04435)		(0.03173)
%college education and higher		0.68978***		0.69087***		0.70434***		0.79309***
		(0.05075)		(0.05221)		(0.04491)		(0.03077)
Constant	2.02198***	1.40901***	1.97817***	1.41587***	2.04010***	1.46935***	1.99188***	1.39202***
	(0.00650)	(0.03410)	(0.00700)	(0.02900)	(0.00460)	(0.02991)	(0.00608)	(0.03647)
Observations	21450	21450	21450	21450	21450	21450	21450	21450
R-squared	0.92	0.93	0.93	0.94	0.93	0.94	0.84	0.87
T test: Adopt+AdoptxLow=0	0.01512	0.00026	0.01027	-0.00395	0.00478	-0.00253	-0.00591	-0.00575
T-stat_1	1.53108	0.03778	1.04212	-0.51897	0.57228	-0.38857	-0.68793	-0.96320
test: Adopt+AdoptxHigh=0	0.00884	0.00583	0.00563	**0.01186**	0.00466	0.00299	-0.00061	0.00054
T-stat_2	0.86359	0.70658	0.72429	**1.69253**	0.57835	0.46894	-0.06445	0.08356
F test: Adopt=AdoptxLow=AdoptxHigh=0	2.33647	1.45167	1.57218	1.29269	2.14438	2.42349	4.74251	9.12422
Prob > F	0.07163	0.22563	0.19380	0.27496	0.09237	0.06379	0.00262	0.00000

Robust standard errors in parentheses

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

Table 6A: **Public Policy** Exception (**All Areas**) [Dep Var: **LN(emp/pop)** by occupation group Low, Medium, High]
Weighted Least Square [Weight = (sqrt of) # of obs that belong to each occupation group]
Controls are at the occupation group level; Standard errors are clustered by state

	Any Training		School Training		Formal Training		Informal Training	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Adopt(PP)	-0.00631	-0.01586	-0.02445	-0.03229**	-0.02746	-0.03371*	0.00186	0.00829
	(0.02035)	(0.01449)	(0.01610)	(0.01338)	(0.02304)	(0.01746)	(0.01244)	(0.01268)
Adopt(PP)xLow	-0.00328	0.01822	0.02241	0.03764	0.02700	0.03948	-0.03456	-0.04360
	(0.06438)	(0.04540)	(0.05891)	(0.04567)	(0.06378)	(0.04616)	(0.03597)	(0.03278)
Adopt(PP)xHigh	-0.01455	-0.02902	0.02267	0.00751	0.03843**	0.01520	-0.00304	-0.01254
	(0.04305)	(0.04064)	(0.04274)	(0.03989)	(0.01900)	(0.01598)	(0.03019)	(0.02886)
Low	-0.05914	0.07601	-0.15454***	-0.00863	-0.22457***	0.12202*	-0.35291***	-0.32709***
	(0.04381)	(0.07045)	(0.04098)	(0.07356)	(0.04371)	(0.07147)	(0.03251)	(0.06527)
High	-0.67726***	-1.23363***	-0.48587***	-0.93663***	-0.82345***	-0.92423***	-0.40312***	-0.28810***
	(0.02920)	(0.10107)	(0.02865)	(0.12970)	(0.01247)	(0.05249)	(0.02404)	(0.03904)
LowXt	-0.00103***	-0.00096***	-0.00083***	-0.00108***	-0.00143***	-0.00142***	-0.00048***	-0.00067***
	(0.00027)	(0.00026)	(0.00026)	(0.00024)	(0.00027)	(0.00027)	(0.00016)	(0.00020)
HighXt	0.00092***	0.00109***	0.00120***	0.00138***	-0.00023***	-0.00040***	0.00042***	0.00059***
	(0.00016)	(0.00019)	(0.00015)	(0.00022)	(0.00008)	(0.00009)	(0.00013)	(0.00014)
%male		0.11097		0.21828		0.00103		0.67289**
		(0.16201)		(0.20739)		(0.20775)		(0.26864)
%black		0.63782**		0.47451*		0.32000		-0.25701
		(0.25317)		(0.28111)		(0.24824)		(0.25620)
%age18-35		-0.76758***		-0.62261*		-0.64143**		-0.71441**
		(0.28583)		(0.35817)		(0.28544)		(0.34692)
%age36-55		-0.54024**		-0.27883		-0.50323**		-0.99223***
		(0.21868)		(0.28064)		(0.21004)		(0.31726)
%married		-0.24671		-0.09649		-0.18206		-0.03093
		(0.18112)		(0.17349)		(0.12118)		(0.12002)
%union		-0.60541		-0.94298		-0.55707		-0.22821
		(0.48985)		(0.61857)		(0.43914)		(0.28605)
%high school education		0.45442**		0.86930***		0.70454***		-0.51587**
		(0.21065)		(0.26745)		(0.18459)		(0.20392)
%some college education		-0.12362		0.16482		0.38391*		-0.86472***
		(0.28945)		(0.28763)		(0.22896)		(0.32763)
%college education and higher		1.81018***		1.71667***		2.17192***		-0.55286
		(0.32548)		(0.40429)		(0.29170)		(0.34314)
Constant	-1.36499***	-1.18537***	-1.39039***	-1.74105***	-1.25036***	-1.56819***	-1.34962***	-0.48591*
	(0.01705)	(0.32571)	(0.01343)	(0.39866)	(0.01956)	(0.29171)	(0.01051)	(0.26810)
Observations	21450	21450	21450	21450	21450	21450	21450	21450
R-squared	0.83	0.86	0.68	0.72	0.90	0.92	0.82	0.84
T test: Adopt+AdoptxLow=0	-0.00959	0.00236	-0.00204	0.00536	-0.00047	0.00577	-0.03270	-0.03531
T-stat_1	-0.21015	0.06839	-0.04427	0.14113	-0.01096	0.18081	-1.10492	-1.31075
test: Adopt+AdoptxHigh=0	-0.02086	-0.04489	-0.00178	-0.02477	0.01097	-0.01851	-0.00118	-0.00425
T-stat_2	-0.34524	-0.89249	-0.03356	-0.53659	0.28945	-0.65670	-0.04071	-0.16413
F test: Adopt=AdoptxLow=AdoptxHigh=0	0.96441	1.16216	1.78083	2.34897	4.63779	2.70958	1.05068	1.29677
Prob > F	0.40840	0.32255	0.14840	0.07045	0.00303	0.04345	0.36880	0.27358

Robust standard errors in parentheses

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

Table 6B: **Public Policy** Exception (**All Areas**) [Dep Var: **LN(avg wage)** by occupation group Low, Medium, High]

Weighted Least Square [Weight = (sqrt of) # of obs that belong to each occupation group that have valid wage information]

Controls are at the occupation group level; Standard errors are clustered by state

	Any Training		School Training		Formal Training		Informal Training	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Adopt(PP)	-0.00768	-0.00897	-0.00808	-0.00990*	-0.00602	-0.00745	0.00192	-0.00053
	(0.00704)	(0.00612)	(0.00775)	(0.00589)	(0.00829)	(0.00817)	(0.00669)	(0.00556)
Adopt(PP)xLow	0.00617	0.00350	0.00611	0.00383	0.00235	0.00091	-0.02372*	-0.01772*
	(0.01257)	(0.00858)	(0.01429)	(0.00967)	(0.01376)	(0.01133)	(0.01296)	(0.00924)
Adopt(PP)xHigh	-0.00632	-0.00533	0.00047	0.00206	0.00401	0.00326	0.00425	-0.00138
	(0.01297)	(0.00846)	(0.01472)	(0.01260)	(0.01236)	(0.01131)	(0.01888)	(0.01250)
Low	-0.29825***	-0.18970***	-0.30721***	-0.19921***	-0.37092***	-0.19735***	-0.29176***	-0.20146***
	(0.00863)	(0.01192)	(0.00954)	(0.01043)	(0.00883)	(0.01126)	(0.01119)	(0.01074)
High	0.20221***	-0.00026	0.29254***	0.05766***	0.18569***	0.09153***	0.02744**	0.02024**
	(0.00986)	(0.01132)	(0.01145)	(0.01088)	(0.00818)	(0.00948)	(0.01219)	(0.00789)
LowXt	-0.00039***	-0.00041***	-0.00028***	-0.00030***	-0.00027***	-0.00025***	0.00061***	0.00050***
	(0.00006)	(0.00005)	(0.00006)	(0.00005)	(0.00007)	(0.00006)	(0.00006)	(0.00005)
HighXt	0.00048***	0.00063***	0.00020***	0.00040***	0.00015**	0.00014**	0.00003	0.00007
	(0.00005)	(0.00004)	(0.00006)	(0.00005)	(0.00006)	(0.00006)	(0.00009)	(0.00006)
%male		0.32715***		0.28678***		0.22375***		0.24672***
		(0.01713)		(0.01972)		(0.01950)		(0.01842)
%black		-0.09594***		-0.06495		-0.05263		-0.11307***
		(0.03562)		(0.04399)		(0.03701)		(0.04376)
%age18-35		-0.16297***		-0.17494***		-0.17622***		-0.11790***
		(0.04129)		(0.05097)		(0.03447)		(0.01974)
%age36-55		0.04693		0.02323		0.05149*		0.10073***
		(0.03037)		(0.03657)		(0.02670)		(0.02310)
%married		0.12932***		0.13456***		0.13272***		0.17900***
		(0.02282)		(0.02365)		(0.02100)		(0.01192)
%union		0.28358***		0.27946***		0.29296***		0.26719***
		(0.04403)		(0.05142)		(0.04184)		(0.02969)
%high school education		0.34283***		0.33291***		0.27857***		0.21685***
		(0.05648)		(0.05858)		(0.04056)		(0.02233)
%some college education		0.39453***		0.40539***		0.35348***		0.37829***
		(0.05146)		(0.05869)		(0.04538)		(0.03261)
%college education and higher		0.69130***		0.69222***		0.70415***		0.80379***
		(0.05117)		(0.05315)		(0.04594)		(0.02889)
Constant	2.02469***	1.41684***	1.98687***	1.43125***	2.05068***	1.48768***	2.00850***	1.39861***
	(0.00456)	(0.03267)	(0.00528)	(0.02805)	(0.00564)	(0.03248)	(0.00373)	(0.02680)
Observations	21450	21450	21450	21450	21450	21450	21450	21450
R-squared	0.92	0.93	0.93	0.94	0.93	0.94	0.84	0.87
T test: Adopt+AdoptxLow=0	-0.00151	-0.00547	-0.00198	-0.00607	-0.00366	-0.00654	-0.02179	-0.01825
T-stat_1	-0.16410	-0.75566	-0.19248	-0.69038	-0.41081	-0.95395	-1.47010	-1.65947
test: Adopt+AdoptxHigh=0	-0.01401	-0.01430	-0.00762	-0.00784	-0.00201	-0.00419	0.00617	-0.00191
T-stat_2	-1.01435	-1.29902	-0.55199	-0.58441	-0.19974	-0.50999	0.38727	-0.17678
F test: Adopt=AdoptxLow=AdoptxHigh=0	0.72832	1.16488	0.62079	1.03736	0.32662	0.67437	1.61337	2.25321
Prob > F	0.53493	0.32148	0.60147	0.37469	0.80612	0.56764	0.18392	0.08000

Robust standard errors in parentheses

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

Table 7A: **Good Faith** Exception (**Highly Populated Areas: 1M+**) [Dep Var: **LN(emp/pop)** by occupation group Low, Medium, High]

Weighted Least Square [Weight = (sqrt of) # of obs that belong to each occupation group]

Controls are at the occupation group level; Standard errors are clustered by state

	Any Training		School Training		Formal Training		Informal Training	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Adopt(IC)	0.00683	0.00020	-0.00914	-0.01088	0.01475*	0.01642	0.02583*	0.02340
	(0.00652)	(0.01358)	(0.00726)	(0.01236)	(0.00846)	(0.01089)	(0.01491)	(0.01519)
Adopt(IC)xLow	-0.02014	-0.03662	-0.01547	-0.04070	-0.02311	-0.04316	-0.06739***	-0.06963***
	(0.04210)	(0.02970)	(0.04468)	(0.03353)	(0.04646)	(0.03554)	(0.01839)	(0.02216)
Adopt(IC)xHigh	0.03106	0.04439	0.06633*	0.07576***	0.01014	0.00123	-0.00613	-0.00412
	(0.05196)	(0.04416)	(0.03599)	(0.02652)	(0.03471)	(0.02866)	(0.02644)	(0.02499)
Low	-0.32219***	-0.37519***	-0.38442***	-0.40802***	-0.44367***	-0.41826***	-0.53376***	-0.52413***
	(0.03110)	(0.06205)	(0.02823)	(0.05347)	(0.03254)	(0.04563)	(0.01997)	(0.02928)
High	-0.62353***	-0.86755***	-0.39131***	-0.51463***	-0.71411***	-0.71918***	-0.33836***	-0.31639***
	(0.02218)	(0.04570)	(0.02313)	(0.06692)	(0.02172)	(0.02775)	(0.01823)	(0.01688)
LowXt	-0.00049**	-0.00017	-0.00026	-0.00013	-0.00095***	-0.00076***	-0.00013	-0.00023
	(0.00025)	(0.00021)	(0.00022)	(0.00021)	(0.00023)	(0.00022)	(0.00017)	(0.00016)
HighXt	0.00106***	0.00094***	0.00128***	0.00097***	-0.00016	-0.00037***	0.00021	0.00016
	(0.00014)	(0.00015)	(0.00015)	(0.00015)	(0.00010)	(0.00010)	(0.00015)	(0.00015)
%male		-0.18756*		-0.24472*		-0.18727		0.07702
		(0.10906)		(0.14739)		(0.12198)		(0.08583)
%black		-0.12268		-0.17932		-0.15944		-0.03192
		(0.20377)		(0.21849)		(0.21704)		(0.10165)
%age18-35		0.35643*		0.34652***		0.26110*		0.32944***
		(0.19145)		(0.13079)		(0.14178)		(0.05388)
%age36-55		0.29355*		0.34984***		0.22980**		0.28085***
		(0.17813)		(0.11008)		(0.09391)		(0.06821)
%married		-0.21347		-0.14663		-0.23474*		-0.03092
		(0.19581)		(0.14678)		(0.14108)		(0.04894)
%union		0.39232*		0.23227		0.20408		0.04289
		(0.23503)		(0.26582)		(0.18597)		(0.14282)
%high school education		-0.57929***		-0.42960**		-0.46637***		-0.27431***
		(0.20412)		(0.19817)		(0.18069)		(0.08250)
%some college education		-0.90842***		-0.82209***		-0.75776***		-0.32997***
		(0.21111)		(0.20823)		(0.20460)		(0.09647)
%college education and higher		0.13745		0.09582		0.21216		-0.15644
		(0.20601)		(0.22797)		(0.18592)		(0.09821)
Constant	-1.16178***	-0.75730***	-1.21691***	-0.91770***	-1.06907***	-0.75046***	-1.16116***	-1.23824***
	(0.00474)	(0.26611)	(0.00574)	(0.16273)	(0.00892)	(0.15673)	(0.00705)	(0.08604)
Observations	10452	10452	10452	10452	10452	10452	10452	10452
R-squared	0.89	0.90	0.83	0.85	0.94	0.95	0.93	0.94
T test: Adopt+AdoptxLow=0	-0.01331	-0.03642	-0.02461	-0.05159	-0.00836	-0.02674	**-0.04156**	**-0.04623**
T-stat_1	-0.29379	-0.94721	-0.52464	-1.33532	-0.19231	-0.74733	**-3.26846**	**-3.72906**
test: Adopt+AdoptxHigh=0	0.03789	0.04458	**0.05719**	**0.06488**	0.02490	0.01765	0.01970	0.01928
T-stat_2	0.80023	1.22245	**1.83721**	**2.92692**	0.77203	0.66824	1.51103	1.54293
F test: Adopt=AdoptxLow=AdoptxHigh=0	4.10805	0.93057	5.41680	3.05470	6.48318	1.15108	9.46359	8.73200
Prob > F	0.00637	0.42491	0.00101	0.02723	0.00022	0.32693	0.00000	0.00001

Robust standard errors in parentheses

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

Note: Highly Populated Area for GF contains only DE and AZ

Table 7B: **Good Faith** Exception (**Highly Populated Areas: 1M+**) [Dep Var: **LN(avg wage)** by occupation group Low, Medium, High]
Weighted Least Square [Weight = (sqrt of) # of obs that belong to each occupation group that have valid wage information]
Controls are at the occupation group level; Standard errors are clustered by state

	Any Training		School Training		Formal Training		Informal Training	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Adopt(IC)	-0.01313	-0.05155***	-0.00308	-0.03801***	-0.00216	-0.03855***	-0.01004	-0.04583***
	(0.00912)	(0.00779)	(0.00841)	(0.00751)	(0.00588)	(0.00679)	(0.00848)	(0.00466)
Adopt(IC)xLow	-0.02767**	-0.01415*	-0.03804**	-0.02728**	-0.02788	-0.01795	0.01292	0.00519
	(0.01348)	(0.00850)	(0.01921)	(0.01071)	(0.01908)	(0.01598)	(0.01491)	(0.00985)
Adopt(IC)xHigh	0.01110	0.01121	0.00042	0.00393	0.00204	-0.00030	0.02624	0.00707
	(0.01542)	(0.01174)	(0.00866)	(0.01211)	(0.00900)	(0.00688)	(0.01624)	(0.00744)
Low	-0.29208***	-0.20771***	-0.30699***	-0.22269***	-0.37317***	-0.20821***	-0.30373***	-0.19165***
	(0.01284)	(0.00761)	(0.01106)	(0.00669)	(0.00868)	(0.00687)	(0.01608)	(0.01644)
High	0.22085***	0.03945***	0.31126***	0.11110***	0.18736***	0.08335***	-0.00571	0.00232
	(0.00905)	(0.01257)	(0.01029)	(0.01075)	(0.00665)	(0.00702)	(0.00987)	(0.00456)
LowXt	-0.00066***	-0.00061***	-0.00051***	-0.00046***	-0.00055***	-0.00047***	0.00047***	0.00035***
	(0.00010)	(0.00008)	(0.00009)	(0.00007)	(0.00009)	(0.00008)	(0.00008)	(0.00007)
HighXt	0.00030***	0.00045***	0.00010*	0.00028***	0.00007	0.00012**	0.00007	0.00011**
	(0.00005)	(0.00004)	(0.00006)	(0.00004)	(0.00006)	(0.00005)	(0.00007)	(0.00004)
%male		0.31128***		0.25974***		0.24185***		0.24620***
		(0.02155)		(0.02170)		(0.01718)		(0.02731)
%black		-0.11481***		-0.09655***		-0.08533***		-0.12925***
		(0.02837)		(0.02903)		(0.02711)		(0.04032)
%age18-35		-0.14871***		-0.12762***		-0.15767***		-0.10337***
		(0.02440)		(0.03084)		(0.02747)		(0.01886)
%age36-55		0.08545***		0.07891***		0.09616***		0.14602***
		(0.02192)		(0.02802)		(0.02257)		(0.02507)
%married		0.12945***		0.13276***		0.13739***		0.17086***
		(0.01636)		(0.01569)		(0.01346)		(0.01588)
%union		0.30859***		0.32136***		0.25939***		0.20926***
		(0.03541)		(0.03408)		(0.03502)		(0.03298)
%high school education		0.27669***		0.25936***		0.24571***		0.23428***
		(0.03971)		(0.03170)		(0.02953)		(0.02922)
%some college education		0.33122***		0.32509***		0.32912***		0.39247***
		(0.04375)		(0.03680)		(0.03318)		(0.03435)
%college education and higher		0.57515***		0.55242***		0.63869***		0.78448***
		(0.03986)		(0.02951)		(0.02978)		(0.03501)
Constant	2.27386***	1.71605***	2.20595***	1.70296***	2.29190***	1.72683***	2.30501***	1.62060***
	(0.00428)	(0.03857)	(0.00400)	(0.03494)	(0.00282)	(0.03593)	(0.00335)	(0.04435)
Observations	10417	10417	10424	10424	10426	10426	10440	10440
R-squared	0.91	0.93	0.93	0.94	0.92	0.93	0.74	0.81
T test: Adopt+AdoptxLow=0	**-0.04080**	**-0.06570**	**-0.04112**	**-0.06529**	**-0.03004**	**-0.05650**	0.00288	**-0.04064**
T-stat_1	**-3.18052**	**-6.89728**	**-2.48382**	**-4.94043**	**-1.84878**	**-4.43944**	0.24125	**-4.83350**
test: Adopt+AdoptxHigh=0	-0.00203	**-0.04033**	-0.00266	**-0.03407**	-0.00011	**-0.03884**	0.01620	**-0.03876**
T-stat_2	-0.15150	**-3.57496**	-0.33858	**-3.24841**	-0.00894	**-3.64595**	1.08991	**-4.62525**
F test: Adopt=AdoptxLow=AdoptxHigh=0	8.49616	25.54427	3.93849	35.38949	1.52918	30.41652	1.52259	43.67560
Prob > F	0.00001	0.00000	0.00807	0.00000	0.20468	0.00000	0.20639	0.00000

Robust standard errors in parentheses

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

Note: Highly Populated Area for GF contains only DE and AZ

Table 8A: **Good Faith** Exception (**Other Areas: <1M**) [Dep Var: **LN(emp/pop)** by occupation group Low, Medium, High]

Weighted Least Square [Weight = (sqrt of) # of obs that belong to each occupation group]

Controls are at the occupation group level; Standard errors are clustered by state

	Any Training		School Training		Formal Training		Informal Training	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Adopt(IC)	0.04227**	0.04358**	0.01017	0.01203	0.03802**	0.04143***	-0.02728	-0.01054
	(0.02077)	(0.02001)	(0.01986)	(0.02006)	(0.01651)	(0.01562)	(0.02127)	(0.02048)
Adopt(IC)xLow	-0.15270**	-0.14101**	-0.13100**	-0.12494**	-0.14395**	-0.13876**	0.03366	-0.00434
	(0.06045)	(0.05803)	(0.06172)	(0.06093)	(0.06104)	(0.05782)	(0.07591)	(0.06815)
Adopt(IC)xHigh	0.09377**	0.08189**	0.14461***	0.14086***	0.06761*	0.06098*	0.05132*	0.04235
	(0.03759)	(0.03732)	(0.04517)	(0.04303)	(0.03803)	(0.03566)	(0.02738)	(0.02833)
Low	0.09122***	0.11564***	-0.00789	0.00632	-0.07724***	0.05753	-0.28386***	-0.18515***
	(0.01682)	(0.04300)	(0.02043)	(0.03966)	(0.02101)	(0.03653)	(0.03741)	(0.05701)
High	-0.74902***	-0.91654***	-0.56319***	-0.74611***	-0.88646***	-0.98726***	-0.46434***	-0.39545***
	(0.01431)	(0.05796)	(0.01477)	(0.07228)	(0.01263)	(0.02996)	(0.01484)	(0.02288)
LowXt	-0.00091***	-0.00082***	-0.00066***	-0.00075***	-0.00113***	-0.00119***	-0.00055***	-0.00082***
	(0.00014)	(0.00018)	(0.00014)	(0.00020)	(0.00014)	(0.00019)	(0.00013)	(0.00015)
HighXt	0.00053***	0.00048***	0.00094***	0.00098***	-0.00020**	-0.00025**	0.00061***	0.00081***
	(0.00011)	(0.00015)	(0.00012)	(0.00017)	(0.00010)	(0.00011)	(0.00010)	(0.00011)
%male		0.08934		0.36024***		0.31004***		0.65254***
		(0.10667)		(0.12965)		(0.11702)		(0.19893)
%black		0.15241		0.06044		-0.03234		-0.87814***
		(0.18535)		(0.20984)		(0.19786)		(0.24521)
%age18-35		-0.41615***		-0.28913**		-0.47508***		-0.06425
		(0.15113)		(0.13380)		(0.14144)		(0.14099)
%age36-55		-0.17037		0.02156		-0.26839***		-0.17909
		(0.11061)		(0.10503)		(0.10246)		(0.11807)
%married		0.09079		0.13376		0.08350		0.15187*
		(0.09207)		(0.09079)		(0.07134)		(0.07963)
%union		0.40424		0.43213		0.20343		0.09870
		(0.25010)		(0.30379)		(0.24491)		(0.19502)
%high school education		0.01434		0.13797		0.14499		-0.33621***
		(0.20422)		(0.20617)		(0.19142)		(0.12556)
%some college education		-0.12305		-0.06542		0.17427		-0.59544***
		(0.22443)		(0.22052)		(0.21264)		(0.21268)
%college education and higher		0.42119*		0.36999		0.74754***		-0.81745***
		(0.21842)		(0.24362)		(0.18605)		(0.22575)
Constant	-1.40877***	-1.32682***	-1.42541***	-1.68676***	-1.29996***	-1.49234***	-1.35012***	-1.30766***
	(0.00528)	(0.17884)	(0.00501)	(0.13220)	(0.00677)	(0.11130)	(0.01147)	(0.11753)
Observations	17400	17400	17400	17400	17400	17400	17400	17400
R-squared	0.89	0.90	0.79	0.80	0.92	0.92	0.77	0.80
T test: Adopt+AdoptxLow=0	**-0.11043**	**-0.09743**	**-0.12083**	**-0.11292**	**-0.10592**	**-0.09732**	0.00637	-0.01488
T-stat_1	**-2.59816**	**-2.30769**	**-2.51483**	**-2.32318**	**-2.29033**	**-2.13338**	0.11164	-0.28789
test: Adopt+AdoptxHigh=0	**0.13603**	**0.12547**	**0.15478**	**0.15289**	**0.10563**	**0.10241**	0.02404	0.03181
T-stat_2	**2.95819**	**2.87037**	**3.29212**	**3.50213**	**2.13129**	**2.25470**	0.62705	0.84785
F test: Adopt=AdoptxLow=AdoptxHigh=0	3.18164	3.48026	4.44688	5.87568	1.89029	2.42182	2.31792	1.07494
Prob > F	0.02288	0.01519	0.00396	0.00053	0.12881	0.06394	0.07343	0.35827

Robust standard errors in parentheses

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

Table 8B: **Good Faith** Exception (**Other Areas: <1M**) [Dep Var: **LN(avg wage)** by occupation group Low, Medium, High]
Weighted Least Square [Weight = (sqrt of) # of obs that belong to each occupation group that have valid wage information]
Controls are at the occupation group level; Standard errors are clustered by state

	Any Training		School Training		Formal Training		Informal Training	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Adopt(IC)	0.00620	0.01477*	0.02368***	0.02681***	0.02058**	0.02208**	0.02854**	0.02697**
	(0.00795)	(0.00877)	(0.00867)	(0.00923)	(0.00927)	(0.01091)	(0.01135)	(0.01174)
Adopt(IC)xLow	0.01754	0.00607	-0.01648	-0.01882**	-0.01648	-0.01357	-0.01687	-0.01501
	(0.01592)	(0.01002)	(0.01275)	(0.00952)	(0.01144)	(0.01005)	(0.01640)	(0.01214)
Adopt(IC)xHigh	0.00682	-0.00856	-0.02040	-0.02040	-0.00810	-0.01472**	-0.02421**	-0.02177***
	(0.00944)	(0.00969)	(0.01585)	(0.01310)	(0.00712)	(0.00631)	(0.00989)	(0.00628)
Low	-0.28001***	-0.19196***	-0.28282***	-0.19892***	-0.35134***	-0.19340***	-0.29311***	-0.21786***
	(0.00829)	(0.00914)	(0.00835)	(0.00863)	(0.00848)	(0.00987)	(0.00815)	(0.00782)
High	0.17589***	0.01011	0.27329***	0.07840***	0.17852***	0.09768***	0.05042***	0.03189***
	(0.00666)	(0.01029)	(0.00727)	(0.01008)	(0.00468)	(0.00793)	(0.00557)	(0.00345)
LowXt	-0.00027***	-0.00031***	-0.00018***	-0.00020***	-0.00008	-0.00010**	0.00050***	0.00038***
	(0.00005)	(0.00004)	(0.00005)	(0.00004)	(0.00005)	(0.00004)	(0.00006)	(0.00006)
HighXt	0.00052***	0.00062***	0.00024***	0.00039***	0.00031***	0.00028***	0.00009	0.00009*
	(0.00006)	(0.00005)	(0.00006)	(0.00006)	(0.00005)	(0.00005)	(0.00006)	(0.00005)
%male		0.30728***		0.29249***		0.20344***		0.22588***
		(0.01936)		(0.01870)		(0.02027)		(0.01485)
%black		-0.13649***		-0.11435***		-0.09290***		-0.05998*
		(0.02955)		(0.03030)		(0.03107)		(0.03075)
%age18-35		-0.10792***		-0.10988***		-0.11030***		-0.14028***
		(0.02184)		(0.01978)		(0.01574)		(0.01607)
%age36-55		0.06544***		0.07612***		0.08676***		0.07308***
		(0.01784)		(0.01717)		(0.01730)		(0.01604)
%married		0.16800***		0.17755***		0.17170***		0.16745***
		(0.01397)		(0.01374)		(0.01350)		(0.01430)
%union		0.31530***		0.33865***		0.32641***		0.32243***
		(0.03366)		(0.03787)		(0.03684)		(0.02659)
%high school education		0.23544***		0.20539***		0.19514***		0.18990***
		(0.02760)		(0.02593)		(0.02371)		(0.01858)
%some college education		0.32092***		0.29932***		0.29205***		0.33623***
		(0.02890)		(0.02701)		(0.02232)		(0.02458)
%college education and higher		0.52218***		0.48494***		0.58455***		0.74991***
		(0.03024)		(0.02727)		(0.02962)		(0.02267)
Constant	2.02348***	1.46505***	1.98317***	1.46132***	2.04129***	1.49634***	2.00879***	1.46987***
	(0.00371)	(0.02463)	(0.00320)	(0.02544)	(0.00283)	(0.02925)	(0.00338)	(0.02072)
Observations	17382	17382	17383	17383	17380	17380	17384	17384
R-squared	0.85	0.88	0.88	0.90	0.87	0.89	0.74	0.79
T test: Adopt+AdoptxLow=0	0.02373	0.02084	0.00721	0.00799	0.00410	0.00852	0.01167	0.01196
T-stat_1	1.61293	1.54814	0.64278	0.82305	0.38968	0.79812	0.86811	0.96087
test: Adopt+AdoptxHigh=0	0.01301	0.00621	0.00328	0.00641	0.01248	0.00736	0.00433	0.00520
T-stat_2	0.98288	0.44648	0.24280	0.49835	1.54540	0.78623	0.51583	0.56014
F test: Adopt=AdoptxLow=AdoptxHigh=0	1.31935	1.40074	2.51290	3.09746	1.69527	2.25702	2.93683	4.03617
Prob > F	0.26607	0.24048	0.05661	0.02567	0.16566	0.07960	0.03195	0.00703

Robust standard errors in parentheses

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

Table 9A: **Implied Contract** Exception (**Highly Populated Areas: 1M+**) [Dep Var: **LN(emp/pop)** by occupation group Low, Medium, High]

Weighted Least Square [Weight = (sqrt of) # of obs that belong to each occupation group]

Controls are at the occupation group level; Standard errors are clustered by state

	Any Training		School Training		Formal Training		Informal Training	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Adopt(IC)	-0.02600*	-0.02272	-0.04908***	-0.04875***	-0.01622	-0.01285	-0.02186	-0.02167
	(0.01471)	(0.01423)	(0.01667)	(0.01566)	(0.01605)	(0.01601)	(0.02150)	(0.02116)
Adopt(IC)xLow	-0.05365*	-0.05590**	-0.01931	-0.01663	-0.04838	-0.04527	-0.02580	-0.02628
	(0.03043)	(0.02560)	(0.03095)	(0.02936)	(0.03522)	(0.03156)	(0.03422)	(0.03326)
Adopt(IC)xHigh	0.06605**	0.06416***	0.09820***	0.10116***	0.02511	0.02143	0.00526	0.00429
	(0.02911)	(0.02353)	(0.03065)	(0.02656)	(0.02781)	(0.02366)	(0.02898)	(0.02732)
Low	-0.29176***	-0.34941***	-0.37495***	-0.40966***	-0.41714***	-0.39985***	-0.53192***	-0.53165***
	(0.02726)	(0.05201)	(0.02531)	(0.05070)	(0.02860)	(0.04063)	(0.02852)	(0.03806)
High	-0.65958***	-0.88408***	-0.43993***	-0.56448***	-0.72795***	-0.73942***	-0.34310***	-0.32498***
	(0.02956)	(0.03935)	(0.03186)	(0.06870)	(0.02047)	(0.02441)	(0.02893)	(0.02871)
LowXt	-0.00041*	-0.00011	-0.00024	-0.00015	-0.00088***	-0.00074***	-0.00010	-0.00017
	(0.00024)	(0.00020)	(0.00023)	(0.00022)	(0.00023)	(0.00022)	(0.00018)	(0.00019)
HighXt	0.00095***	0.00084***	0.00113***	0.00083***	-0.00020	-0.00040***	0.00019	0.00015
	(0.00014)	(0.00014)	(0.00014)	(0.00014)	(0.00013)	(0.00012)	(0.00014)	(0.00015)
%male		-0.16229		-0.17725		-0.13714		0.03291
		(0.10572)		(0.13183)		(0.10807)		(0.10008)
%black		-0.06578		-0.00244		-0.12379		0.03366
		(0.22404)		(0.24877)		(0.22355)		(0.09972)
%age18-35		0.38897**		0.30636**		0.25865**		0.32875***
		(0.19035)		(0.13407)		(0.12361)		(0.05218)
%age36-55		0.32343**		0.30017***		0.21427***		0.26794***
		(0.15170)		(0.09283)		(0.07783)		(0.07161)
%married		-0.23546		-0.17395		-0.25410**		-0.04865
		(0.14686)		(0.11143)		(0.11463)		(0.05539)
%union		0.58079**		0.40461*		0.28554		0.03303
		(0.22782)		(0.23611)		(0.18790)		(0.12665)
%high school education		-0.52086***		-0.31832*		-0.41555***		-0.25342***
		(0.16405)		(0.16474)		(0.16092)		(0.07965)
%some college education		-0.82363***		-0.71611***		-0.69576***		-0.30200***
		(0.17992)		(0.18909)		(0.17790)		(0.10438)
%college education and higher		0.14301		0.17913		0.23251		-0.07889
		(0.17508)		(0.20816)		(0.16517)		(0.07646)
Constant	-1.14829***	-0.82390***	-1.18852***	-0.96193***	-1.06085***	-0.78840***	-1.14626***	-1.21616***
	(0.00938)	(0.21873)	(0.01277)	(0.14106)	(0.00937)	(0.13188)	(0.01679)	(0.10176)
Observations	10452	10452	10452	10452	10452	10452	10452	10452
R-squared	0.89	0.90	0.84	0.85	0.94	0.95	0.93	0.93
T test: Adopt+AdoptxLow=0	**-0.07966**	**-0.07862**	**-0.06839**	**-0.06538**	**-0.06460**	**-0.05812**	**-0.04766**	**-0.04795**
T-stat_1	**-2.80743**	**-3.23943**	**-2.42314**	**-2.40338**	**-2.31416**	**-2.34897**	**-2.13502**	**-2.20531**
test: Adopt+AdoptxHigh=0	0.04005	0.04145	**0.04911**	**0.05241**	0.00888	0.00858	-0.01660	-0.01738
T-stat_2	1.27160	1.64395	**1.72267**	**1.98999**	0.30066	0.33623	-0.87828	-0.98518
F test: Adopt=AdoptxLow=AdoptxHigh=0	3.36663	4.20701	4.85650	6.28589	2.62151	2.31756	2.33607	2.39355
Prob > F	0.01777	0.00555	0.00223	0.00029	0.04895	0.07349	0.07170	0.06642

Robust standard errors in parentheses

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

Table 9B: **Implied Contract** Exception (**Highly Populated Areas: 1M+**) [Dep Var: **LN(avg wage)** by occupation group Low, Medium, High]
Weighted Least Square [Weight = (sqrt of) # of obs that belong to each occupation group that have valid wage information]
Controls are at the occupation group level; Standard errors are clustered by state

	Any Training		School Training		Formal Training		Informal Training	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Adopt(IC)	-0.01091	-0.00512	-0.00629	-0.00702	0.00041	0.00071	0.00785	0.00979
	(0.00986)	(0.00702)	(0.00993)	(0.00657)	(0.00739)	(0.00650)	(0.01081)	(0.00715)
Adopt(IC)xLow	0.00236	-0.00894	-0.01224	-0.01648*	-0.01866	-0.01883*	-0.02172	-0.02235**
	(0.01787)	(0.00974)	(0.01750)	(0.00935)	(0.01350)	(0.01087)	(0.01835)	(0.00964)
Adopt(IC)xHigh	0.01090	-0.00466	0.00629	0.00828	-0.00583	-0.01150*	-0.01113	-0.01771**
	(0.01019)	(0.00783)	(0.00893)	(0.00802)	(0.00793)	(0.00647)	(0.01473)	(0.00744)
Low	-0.30002***	-0.20479***	-0.30770***	-0.21807***	-0.36743***	-0.19883***	-0.28650***	-0.17559***
	(0.01442)	(0.00962)	(0.01435)	(0.00807)	(0.01067)	(0.00980)	(0.01269)	(0.01357)
High	0.21635***	0.04396***	0.30733***	0.10443***	0.19167***	0.08963***	0.00785	0.01591***
	(0.00771)	(0.01213)	(0.00789)	(0.00931)	(0.00458)	(0.00676)	(0.00793)	(0.00602)
LowXt	-0.00066***	-0.00059***	-0.00049***	-0.00043***	-0.00052***	-0.00045***	0.00051***	0.00038***
	(0.00009)	(0.00008)	(0.00008)	(0.00007)	(0.00009)	(0.00008)	(0.00010)	(0.00008)
HighXt	0.00028***	0.00046***	0.00009	0.00027***	0.00008	0.00014***	0.00009*	0.00014***
	(0.00006)	(0.00005)	(0.00006)	(0.00005)	(0.00005)	(0.00005)	(0.00005)	(0.00004)
%male		0.31555***		0.26755***		0.24678***		0.24899***
		(0.02308)		(0.02158)		(0.01736)		(0.02884)
%black		-0.09814***		-0.07532**		-0.07445**		-0.13495***
		(0.03469)		(0.03644)		(0.03458)		(0.03636)
%age18-35		-0.15972***		-0.13550***		-0.15950***		-0.10534***
		(0.03166)		(0.03825)		(0.02806)		(0.01851)
%age36-55		0.07839***		0.07213**		0.09453***		0.14368***
		(0.02492)		(0.03011)		(0.02351)		(0.02340)
%married		0.12464***		0.12580***		0.13389***		0.17116***
		(0.01730)		(0.01637)		(0.01574)		(0.01502)
%union		0.32028***		0.33807***		0.26928***		0.21827***
		(0.03528)		(0.03503)		(0.03645)		(0.03087)
%high school education		0.28977***		0.27428***		0.25567***		0.22892***
		(0.04031)		(0.03920)		(0.02994)		(0.02835)
%some college education		0.34371***		0.34521***		0.34179***		0.38787***
		(0.04085)		(0.04229)		(0.03594)		(0.03354)
%college education and higher		0.58827***		0.56924***		0.64918***		0.77993***
		(0.03364)		(0.03157)		(0.02978)		(0.03579)
Constant	2.28171***	1.71451***	2.21127***	1.69829***	2.29163***	1.71611***	2.29586***	1.61557***
	(0.00673)	(0.03802)	(0.00699)	(0.03255)	(0.00442)	(0.03211)	(0.00665)	(0.04368)
Observations	10417	10417	10424	10424	10426	10426	10440	10440
R-squared	0.91	0.93	0.93	0.94	0.92	0.93	0.74	0.81
T test: Adopt+AdoptxLow=0	-0.00855	-0.01406	-0.01853	**-0.02350**	-0.01825	**-0.01812**	-0.01388	-0.01256
T-stat_1	-0.53555	-1.13882	-1.34270	**-2.07658**	-1.51762	**-1.73918**	-0.94564	-1.30717
test: Adopt+AdoptxHigh=0	-0.00000	-0.00978	0.00001	0.00127	-0.00543	-0.01079	-0.00329	-0.00791
T-stat_2	-0.00024	-0.98811	0.00083	0.15178	-0.51599	-1.24149	-0.22071	-0.82024
F test: Adopt=AdoptxLow=AdoptxHigh=0	0.62090	0.82768	0.79131	1.48232	1.31613	2.24634	0.69406	3.84754
Prob > F	0.60141	0.47840	0.49854	0.21714	0.26715	0.08077	0.55555	0.00915

Robust standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 10A: **Implied Contract** Exception (**Other Areas: <1M**) [Dep Var: **LN(emp/pop)** by occupation group Low, Medium, High]

Weighted Least Square [Weight = (sqrt of) # of obs that belong to each occupation group]

Controls are at the occupation group level; Standard errors are clustered by state

	Any Training		School Training		Formal Training		Informal Training	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Adopt(IC)	-0.01434	-0.01809	-0.03183**	-0.03505***	-0.02057	-0.01811	-0.06603***	-0.05230**
	(0.01283)	(0.01161)	(0.01268)	(0.01164)	(0.01557)	(0.01532)	(0.02194)	(0.02265)
Adopt(IC)xLow	-0.00897	0.00143	0.02190	0.02212	0.01615	0.00984	0.13565***	0.09420**
	(0.03461)	(0.02976)	(0.03847)	(0.03280)	(0.04181)	(0.03714)	(0.04592)	(0.04251)
Adopt(IC)xHigh	0.02521	0.00776	0.04168	0.03195	0.00096	-0.00855	0.03268	0.03520
	(0.03087)	(0.02803)	(0.03177)	(0.03123)	(0.02663)	(0.02287)	(0.02724)	(0.03139)
Low	0.07899***	0.09245*	-0.03118	-0.01990	-0.10005***	0.04899	-0.34228***	-0.23113***
	(0.02332)	(0.05073)	(0.02898)	(0.05209)	(0.02969)	(0.03967)	(0.03743)	(0.05888)
High	-0.74710***	-0.89302***	-0.56225***	-0.70989***	-0.87798***	-0.97511***	-0.47262***	-0.41034***
	(0.02027)	(0.06241)	(0.01811)	(0.08543)	(0.01595)	(0.03260)	(0.02016)	(0.02641)
LowXt	-0.00093***	-0.00087***	-0.00078***	-0.00087***	-0.00123***	-0.00127***	-0.00100***	-0.00113***
	(0.00016)	(0.00021)	(0.00017)	(0.00026)	(0.00018)	(0.00025)	(0.00022)	(0.00022)
HighXt	0.00046***	0.00041**	0.00084***	0.00088***	-0.00018	-0.00019	0.00051***	0.00069***
	(0.00015)	(0.00020)	(0.00015)	(0.00021)	(0.00013)	(0.00015)	(0.00013)	(0.00015)
%male		0.09287		0.34869**		0.32165**		0.65232***
		(0.11587)		(0.14166)		(0.12962)		(0.19254)
%black		0.30651**		0.24593		0.16035		-0.63874***
		(0.13784)		(0.16607)		(0.13779)		(0.22626)
%age18-35		-0.52762***		-0.38825***		-0.57731***		-0.08745
		(0.15322)		(0.12689)		(0.13404)		(0.13451)
%age36-55		-0.14578		0.08059		-0.24929***		-0.17384
		(0.10157)		(0.11037)		(0.09067)		(0.10821)
%married		0.10449		0.16362		0.05794		0.15717*
		(0.10026)		(0.10630)		(0.06926)		(0.08051)
%union		0.51847*		0.55351		0.29360		0.12608
		(0.31250)		(0.38153)		(0.31536)		(0.17938)
%high school education		0.04449		0.20864		0.22311		-0.28625***
		(0.22297)		(0.21740)		(0.17833)		(0.10197)
%some college education		-0.19059		-0.07272		0.20416		-0.52304***
		(0.23779)		(0.21108)		(0.16718)		(0.15358)
%college education and higher		0.39701*		0.30609		0.84674***		-0.74247***
		(0.23541)		(0.29921)		(0.15900)		(0.18193)
Constant	-1.38905***	-1.27572***	-1.39806***	-1.67853***	-1.27594***	-1.49213***	-1.30105***	-1.31433***
	(0.01127)	(0.23536)	(0.01234)	(0.15527)	(0.01388)	(0.12909)	(0.01957)	(0.10079)
Observations	17400	17400	17400	17400	17400	17400	17400	17400
R-squared	0.88	0.89	0.77	0.78	0.91	0.92	0.78	0.81
T test: Adopt+AdoptxLow=0	-0.02331	-0.01666	-0.00994	-0.01293	-0.00442	-0.00827	**0.06961**	**0.04190**
T-stat_1	-0.90611	-0.71988	-0.33012	-0.47628	-0.15182	-0.32744	**2.48919**	**1.65705**
test: Adopt+AdoptxHigh=0	0.01086	-0.01033	0.00985	-0.00310	-0.01961	-0.02666	**-0.03335**	-0.01710
T-stat_2	0.27538	-0.29530	0.25052	-0.08539	-0.53467	-0.88067	**-1.85595**	-0.79199
F test: Adopt=AdoptxLow=AdoptxHigh=0	1.60697	1.52825	4.86647	4.33754	1.45733	1.50288	3.89664	2.02207
Prob > F	0.18543	0.20489	0.00220	0.00462	0.22404	0.21156	0.00854	0.10848

Robust standard errors in parentheses

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

Table 10B: **Implied Contract** Exception (**Other Areas: <1M**) [Dep Var: **LN(avg wage)** by occupation group Low, Medium, High]
Weighted Least Square [Weight = (sqrt of) # of obs that belong to each occupation group that have valid wage information]
Controls are at the occupation group level; Standard errors are clustered by state

	Any Training		School Training		Formal Training		Informal Training	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Adopt(IC)	-0.00356	0.00860	0.00307	0.00828	0.00589	0.00996	0.02336***	0.01665**
	(0.00902)	(0.00598)	(0.00869)	(0.00728)	(0.00661)	(0.00648)	(0.00887)	(0.00651)
Adopt(IC)xLow	0.02525	-0.00445	0.01815	-0.00476	0.00313	-0.01114	-0.03365**	-0.02599***
	(0.01720)	(0.00793)	(0.01488)	(0.00956)	(0.01143)	(0.00870)	(0.01467)	(0.00841)
Adopt(IC)xHigh	-0.00155	-0.01308*	-0.00928	-0.00728	-0.00998	-0.01037**	-0.02767***	-0.01858***
	(0.00850)	(0.00761)	(0.01097)	(0.00931)	(0.00659)	(0.00477)	(0.00859)	(0.00493)
Low	-0.28927***	-0.18941***	-0.29265***	-0.19850***	-0.35453***	-0.18961***	-0.28001***	-0.20835***
	(0.01133)	(0.00957)	(0.01056)	(0.00983)	(0.00888)	(0.01037)	(0.01173)	(0.00918)
High	0.17750***	0.01403	0.27503***	0.07790***	0.18206***	0.09940***	0.05977***	0.03809***
	(0.00749)	(0.01086)	(0.00831)	(0.01104)	(0.00450)	(0.00750)	(0.00709)	(0.00409)
LowXt	-0.00035***	-0.00029***	-0.00024***	-0.00019***	-0.00010*	-0.00007	0.00061***	0.00047***
	(0.00007)	(0.00005)	(0.00006)	(0.00005)	(0.00006)	(0.00005)	(0.00008)	(0.00006)
HighXt	0.00053***	0.00067***	0.00026***	0.00041***	0.00034***	0.00032***	0.00018***	0.00015***
	(0.00006)	(0.00005)	(0.00006)	(0.00006)	(0.00005)	(0.00005)	(0.00006)	(0.00005)
%male		0.30841***		0.29272***		0.20828***		0.22353***
		(0.01889)		(0.01788)		(0.01939)		(0.01468)
%black		-0.14059***		-0.11146***		-0.09700***		-0.07642***
		(0.02572)		(0.02595)		(0.02487)		(0.02780)
%age18-35		-0.10606***		-0.11068***		-0.10988***		-0.13906***
		(0.02205)		(0.01971)		(0.01545)		(0.01581)
%age36-55		0.06548***		0.07525***		0.08673***		0.07453***
		(0.01815)		(0.01761)		(0.01740)		(0.01623)
%married		0.16682***		0.17622***		0.17097***		0.16720***
		(0.01422)		(0.01404)		(0.01362)		(0.01401)
%union		0.31564***		0.33810***		0.32566***		0.31231***
		(0.03413)		(0.03900)		(0.03863)		(0.02470)
%high school education		0.23424***		0.20749***		0.19780***		0.18375***
		(0.02847)		(0.02631)		(0.02400)		(0.01717)
%some college education		0.32154***		0.30161***		0.29399***		0.32953***
		(0.03053)		(0.02832)		(0.02256)		(0.02221)
%college education and higher		0.52341***		0.49007***		0.58631***		0.74448***
		(0.03111)		(0.02804)		(0.02975)		(0.02137)
Constant	2.02274***	1.45744***	1.98010***	1.45498***	2.03662***	1.48549***	1.99233***	1.46503***
	(0.00849)	(0.02549)	(0.00817)	(0.02543)	(0.00653)	(0.02977)	(0.00843)	(0.02097)
Observations	17382	17382	17383	17383	17380	17380	17384	17384
R-squared	0.85	0.88	0.88	0.90	0.87	0.89	0.74	0.79
T test: Adopt+AdoptxLow=0	**0.02169**	0.00414	**0.02122**	0.00353	0.00902	-0.00118	-0.01030	-0.00934
T-stat_1	**2.01155**	0.64493	**2.16342**	0.55135	1.06835	-0.18921	-1.05363	-1.30266
test: Adopt+AdoptxHigh=0	-0.00511	-0.00448	-0.00620	0.00101	-0.00409	-0.00041	-0.00431	-0.00193
T-stat_2	-0.36741	-0.41202	-0.50660	0.10861	-0.35601	-0.05290	-0.57759	-0.33505
F test: Adopt=AdoptxLow=AdoptxHigh=0	1.53402	2.31325	1.92019	0.55468	2.03687	2.18362	3.83718	5.10548
Prob > F	0.20341	0.07388	0.12390	0.64496	0.10639	0.08772	0.00927	0.00157

Robust standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%