Default Rules: The Case of Wrongful Discharge Laws*

W. Bentley Macleod — Columbia University and IZA

Voraprapa Nakavachara — University of Southern California

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Abstract

This paper provides an empirical analysis of the effects of employment protection on the US labor market. Lazear (1990) has argued that in a frictionless world, private parties should be able to contract around these rules, and hence theoretically there should be no effect. Autor, Donohue and Schwab (2006) have shown, consistent with many earlier studies, that these laws have a negative impact on employment, particularly for individuals with marginal attachment to the workforce. What seems to be puzzing to us is that if the expected effects are zero or negative, then why do such rules continue to find wide spread support by legislatures? In this paper we discuss some of the theories that explain why such laws might be beneficial, and show that indeed for individuals in occupations characterized by high human capital investment, the effect of the laws are either zero or *positive*.

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1 Introduction

One of the most vexing public policy issues is the extent to which governments should intervene in the employment relationship. All countries have laws that provide varying degrees of employment protection, even though there is a wide consensus among economists that such rules tend to reduce employment. For example, the 1994 OECD jobs study called for a general reduction in the rules, yet in that year the United States had just completed a decade of strengthening its wrongful discharge laws. Why do legislatures continue to support employment protection, despite this advice from economists?

In this paper we find that one explanation may be that the law's impact depends upon the characteristics of the employment relationship. In particular we shall present evidence that in occupations associated with high investments into human capital, wrongful discharge law (WDL) may increase employment, while it has a negative effect upon occupations with lower levels of human capital.

From the perspective of the economics of contract both of these results are surprising. Edward Lazear (1990)'s theoretical model suggests that in a Coasean 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) model WDL as a firing costs, and show that it has a much stronger effect upon firing decisions, than upon hiring decisions. Hence, Bentolila and Bertola (1990) find that firings costs have important consequences for the dynamics of employment, but little impact upon long run employment.[1]

However, these theories are not models of the *law,* but are rather reduced form representations of employment law. In practice employment law is very complex, with a large number of rules affecting almost every aspect of the job, such as safety rules, working time rules, maternity leave and so on. Moreover, as Schwartz and Scott (2003) observed,

[1] See Bertola (2004) for an extention of this work to risk averse workers. In that case EPL plays a role in reallocating 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.

there is no accepted general theory of contract law. Rather, for each legal rule one needs to ask what are the costs and the benefits of adoption.

In the context of employment, the common law default rule in the United States is employment at will. In principal this rule works as follows. If an employer hires an employee, and there is no formal contract, then both parties may terminate the relationship whenever they wish, and without cause. As Richard Epstein (1984) laments, in practice there are a number of exceptions to this common law rule which may make it difficult for the employer to dismiss a worker in practice. Epstein (1984) argues that such exceptions make no economic sense. If parties would benefit from restrictions upon the right of separation then they can write a long term contract specifying the conditions under which termination can occur.

Of course, negotiating and writing up a complete employment contract is costly. One prominent theory of contract law holds that the default rule should be set to reflect the desires of the average employment relationship - the so called *majoritarian* default rule.[2] Parties who wish to be ruled by employment-at-will do not need an explicit contract, and hence save upon negotiation and drafting costs. One would change the default rule only if one thought that the majority of new matches would prefer a different rule. Notice, that this theory unambiguously predicts that any *change* in the rule would adversely affect current matches since by revealed preference they preferred the previous rule.

The only alternative to this theory is the hypothesis that parties make errors when drafting an agreement, and hence judicial intervention can improve *existing* contracts. Most law and economics scholars are quite hostile to this view point, particularly since it runs counter to the underlying reason for the right to contract privately - parties can then tailor the contract to their specific needs. However, there are certainly examples of poorly drafted contracts that the courts can improve upon - the question is whether the number of times where their intervention is beneficial is outweighed by the circumstances where court intervention decreases the performance of a relationship. The answer to this question is necessarily empirical. We find that for occupations with high level of human capital investment, some legal interventions may enhance productive efficiency.

Our agenda is as follows. Next, we discuss the common law changes that occurred

[2] These is a large literature on this rule. See for example Goetz and Scott (1980) and Ayres and Gertner (1989) for prominent papers by legal scholars. Early economic models of default rules include Rogerson (1984), and Shavell (1984).

in the United States from 1983 to 1994 that are the subject of our study, and the predicted theoretical consequences of these laws. We then review the previous empirical studies of the impact of WDL on labor market performance. Finally, we discuss the data, followed by our empirical methodology, and results.

2 The Economics of Contract *Law*

The common law default for an employment relationship with no explicit contract is employment at will. Over the years, legislators have introduced a number of *exceptions* to this rule, namely situations where the default is not at-will. Besides these state court ruling exceptions, the US has passed some federal laws (affect the whole country at the same time) that protect specific categories of workers against dismissals. For example there have been various Civil Rights Acts that protect dismissal based upon race or gender (Donohue III and Siegelman (1991)). Oyer and Schaefer (2000) finds that in response firms used mass layoffs rather than individual dismissal of protected persons. Chay (1998) finds evidence that this act did improve the economic welfare of African Americans. DeLeire (2000), Acemoglu and Angrist (2001), and Jolls and Prescott (2004) show that the American with disabilities act harmed these individuals.

There are three classes of at-will exceptions, namely public policy, implied contract, and good faith exceptions. These exceptions, if recognized, apply protection for all classes of workers in the state. The public policy exception to employment at will deems a termination to be wrongful if it is a response to an employee's conduct that is not favored by employer but is protected by law. The exception also covers the case that 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.[3] 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." Both Miles (2000) and Autor, Donohue, and Schwab (2006) find that this law has no significant impact upon labor market

[3] Page 78.

outcomes. This result is likely due to the small number of situations to which it would apply.

All these rules address issues of public policy, and hence do not directly address the default law question which is concerned with efficiency justification for judicial intervention. In this paper we focus on two exceptions to the rule of employment-at-will: the implied contract rule, and the rule of good faith termination.

2.1 The Implied Contract Rule

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.[4] 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 is simply requiring the employer not to mislead the employee, and hence in principal should be efficiency enhancing. The rule is problematic if in fact the employer has erred and does not have an efficient employment terms in the employee handbook. A difficulty that employers faced after the passage of this rule is that if the original handbook was poorly designed, then they cannot correct the book with the express agreement of the employees. This agreement may be difficult to secure.

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 handbook. However, employee handbooks are the not only situation in which there is an implied contract. The case of Pugh v. See's Candy established the principle that a long employment with regular promotion establishes a long term contract.[5] Thus, the employer can only dismiss an employee with cause in these case. What is interesting about the Pugh case is that the reason for dismissal appeared to be capricious. Pugh simply reported to his company that his current supervisor was a

[4] 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).

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

convicted embezzler. The supervisor subsequently fired Pugh. It was ruled at court that this fact was not sufficient for him to win the case, but that the length of good service was sufficient to establish an implied contract, and hence the courts 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 placing a bar on dismissing long term employees who may not fit in, of if delinquent in their performance, the employers are unable to provide sufficient evidence 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 the employer, then we might get a positive outcome on welfare of worker. The size of this positive outcome would be larger for relationships where turnover is costly due to relationship specific investments. Workers are more likely to invest in the firm if they rely upon being treated fairly, which in turn would increase worker productivity and hence employment.

Also, when employer evaluation of employee performance an employer's objectivity can have an impact upon both the productivity of the employee and her wage, as shown by MacLeod (2003) (see section III). The implied contract rule in essence requires the employer to use a more objective performance measure, that can lead to less conflict and more output.

The empirical evidence is mixed. Early work by Dertouzos and Karoly (1992) and a more recent work by Autor, Donohue, and Schwab (2006) observe a moderate negative effect of the implied contract exception on employment. Although Autor, Donohue and Schwab (2006) do get consistently negative effects, particularly for workers with marginal attachment to the workforce, they find that the effect of the law on employment is slightly smaller than Dertouzos and Karoly (1992) - about 0.6% to 0.8% on state's employment per population compared to Dertourzos and Karoly's estimate of 1%. Miles (2000) finds no effects of such law. Autor, Donohue and Schwab (2006) obtain different results because they have a richer data set, and use different definitions for the law in classifying the adoption dates. Their definitions are consistent with those developed by Morriss (1994) and they have updated them until 1999.

The time pattern of the adoption of the implied contract exception to at-will-employment is illustrated in figure 1. See also figure 2 detailing the geographical extent of the changes. We have also plotted the evolution of the public policy exception to employment at will barring employers from dismissing protected workers. It is not completely clear what motivated these changes. Dertouzos and Karoly (1992) have argued that the change in state's legal environment in terms of supply and demand for the wrongful termination doctrines may have driven this. This change in legal environment, if in fact has driven the adoption of the law, will be captured in our regression by the state fixed effects, time fixed effects and the state-specific time trends.

It is interesting to observe that there was much less legislation regarding the good faith exception, the case we turn to now.

2.2 Good Faith Rule

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 do so in a patently unjust manner. The rule is illustrated in the case of Mitford V. Lasala.[6] In this case Mitford was fired from employment as an accountant 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 rule that "good faith and fair dealing... would prohibit firing [employee] for the purpose of preventing him from sharing in future profits."

Currently, courts have typically found a rather narrow application of this rule to the timing of dismissal. 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 being paid retirement benefits.

As we can see from figure 1 and 2, there are much fewer states adopting this law that in the case of the implied contract rule. This may simply reflect the fact that it is less important. However, Dertouzos and Karoly (1992) did find the negative effect of this law

[6] Mitford V. Lasala, 666 P.sd 1000 (Alaska 1963).

on state employment. The effects is approximately 1% for good faith with contract exception - where plaintiff can claim for earning loss compensation only and the effects is about 2% for good faith where tort exception is also recognized - plaintiff can claim for emotional distress and punitive damages. Miles (2000) and Autor, Donohue, and Schwab (2006) find no significant impact of this law.

If good faith rule, in fact, does not just impose some firing costs, but help correct poorly drafted contracts, we could expect to see some positive impact. In the case of *Mitford v. Lasala* the contract was quite clear, and implied that the firm had no obligation to pay the bonus. However, clearly most employees would expect to be paid in such a case, but at the time of writing the agreement simply did not think it would not occur. In such case the courts can enhance productive efficiency by essentially completing an incomplete contract.[7]

2.3 Empirical Implications

At the moment there is no accepted economic theory of this legal rule, in fact law and economics scholars, such as Epstein (1984) and Schwartz and Scott (2003) are in general quite hostile to the notion that courts can enhance contractual performance.

Of course we cannot say that the courts can *never* improve matters. Ultimately, the only way to resolve this issue is through empirical work. The extent to which a good contract can enhance matters depends upon how much is at stake, and how much investment needs to be protected.[8] The optimal long term contract must trade off rigidity to enhance incentives to invest again flexibility to allow better matching. This trade-off and its link to contract law is developed in MacLeod (2005). When parties are expected to make sizable investments into the relationship, then there is a gain from a well specified contract. Hence, in these cases then there should be more employment protection.

However, if matching the person to the right job is more important, then any law that increases the cost of turnover lowers over all efficiency. This implies that the law change can have opposite effects depending upon the characteristics of the job. This

[7] See Kornhauser and MacLeod (2005) for a further discussion of these issues.

[8] There is a large literture in economics that highlight the need to have binding long term contracts when there are large investments - see for example Shavell (1984), Rogerson (1984), Hart and Moore (1988), MacLeod and Malcomson (1993) and Edlin and Reichelstein (1996).

suggests that in aggregate one might not be surprised to see a small effect. In order to see if the law is helpful we need to divide our data into the cases where it is likely to be beneficial, and those where it is not. We cannot directly observe details of worker and employer investment, and hence we adopt two indirect ways of looking at the data.

First, we use data on the level of investment by the firm into the worker that is available with the CPS to dividing jobs into high, medium and low investment. The idea behind this is that if the firm invests, the worker still has to pay attention in order to learn from the training (investment). In other words, investment by firm also requires a corresponding investment by worker. Secondly, we consider the effect of the size of the jurisdiction upon the effect of the law. In large cites the job market is thicker, and hence matching is more efficient. We would expect in that case there will be less benefit to employment protection. In the next section we describe in more detail our data, followed by our empirical strategy.

3 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 US 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 civilian non-institutional population 16 years of age and older. The CPS is the US primary source of labor force statistics for the country's population. 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. They are left out of the sample for eight months. They are again interviewed for another four consecutive months. They then leave the sample permanently. The earning questions are asked to only one-fourth of the workers in the survey. These are the workers in their fourth and 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 often includes supplemental questions on subjects of interest by the Federal and state agencies, private foundations, and 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.

We use the CPS basic monthly files from 1983 to 1994 to construct the employment and wage data series that will be used as the dependent variables in our regression analysis. There are two reasons why we start our data series from 1983, and not earlier. First, the 2-digit detailed occupational 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 occupational 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.[9]

Secondly we use the CPS Job Training Supplement questions from January 1983 to categorize the investment characteristics of the different occupations.[10] By starting our data series after January 1983 we have investment levels defined *before* the period that we study law changes, and hence these categories are not affected by the rule changes. We use these training questions in estimating the average amount of training obtained in each occupation and classifying occupations into three groups. Although one may argue that levels of skill training may change for some occupations the existence of higher protection, one assumption we make here is that the high-investment occupations will still be associated with higher training than the medium and the low-investment occupations, and the medium-investment occupations will still be associated with higher training than the low-investment occuaption, even though the protection has increased.[11]

In the CPS Job Training Supplements, detailed information about training workers needed to obtain to earn their job, and the training received to improve their skills once on

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

[10] Other times when the CPS Job Training Supplements questions were asked were January 1984, and January 1991.

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

that job are gathered. More specifically, we are interested the questions regarding the training which full-time workers received after obtaining their current jobs. Such questions are as follow:

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 the worker received was general or specific.[12] We will assume that it is the combination of both. However, in this paper, we will focus on the specific part of the training (specific investment). We suppose that when investment is high the firm is expecting a longer relationship with the worker, and hence there is more benefit from a well function long term contract. With the above training information, we can calculate, for each occupation, the following:

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

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

[12] According to Becker (1993), general training improves workers' skills that are useful anywhere. Specific training improves workers' skills that are useful only at current employer.

worked in the past. Question 1 (above) is asked only to the employed workers who are at work. To calculate the fraction of workers received any kind of training, we count the number of workers answer YES divided by the number of workers who response to the question by answering YES or NO[13] (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 question divided by all the workers who response to question 1.[14] This may not give truly accurate values of the fraction of workers received employer paid school training, fraction of workers received formal company training, and fraction of workers received informal on-the-job training. But we assume that the rankings of the occupations by such values should be very close to the ones we would get if we were able to calculate the actual fractions.

The rankings of the occupations by each of the above criterion are illustrated in Table 2. Observe that there is a great deal of variation in the level of training, going from more than 70% in the case of teachers and health diagnosis to 5% in private household service occupations when using any kind of training criterion (Table 2A). In table 2B, 2C, and 2D, we illustrate the ranking of occupations using school training, formal training, and informal training criteria calculated by the method explained above. For each criterion, we can categorize occupations into three groups namely, high, medium, and low-investment groups. We can see that for the first three criteria, with a few exceptions, the grouping of occupations are quite similar. For informal training criterion (the last criterion), however, the grouping is almost totally different. Looking at occupations that are classified in the low-investment groups by the first three criteria, about half of them are classified as medium-investment in the last criterion. In the following section, we will do our regression analysis separately for each criterion to see the effects of the laws and to see whether our results are robust to the different measure of investment.

In preparing the monthly employment data, we calculate each occupation's

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

[14] 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.

employment in each state by the state population. The occupation questions are asked to the people in the labor force and the people who are not in the labor force but have worked prior to when the interview was conducted. Thus, there are a number of observations with missing 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 the people not in labor force) when calculating each occupation's employment per state population. Our monthly employment data series start from February 1983 until December 1994.

In preparing the data for the wage regressions, we calculate the average real wage for each occupation by state. Since only one-fourth of the respondents are asked the earning questions, in some occupations, there are not enough observations each month to calculate the average wage information. Therefore, we construct the average wage data to be yearly instead of monthly. Again, to keep the January 1983 training information exogenous, our yearly average wage data for 1983 starts from February whereas for other years the average wages are computed from January until December.

4 Empirical Methodology

To study the effects of the laws on employment for each occupation groups, we use a simple regression approach with a large number of control variables, including state and time fixed effects. We follow Autor, Donohue, and Schwab (2006)'s method in identifying the adoption dates of the law for each state. Krueger (1991) argues that these laws are introduced to address problems with court decisions. If this is true, then the intent of the law is that it improves labor market outcomes, and hence even if adoption is endogenous (we address this issue by including time fixed effects, state fixed effects, and state-specific time trends), we should observe an effect as a *change* in employment as a consequence of the law change.

Thus let us suppose that employment in occupation j satisfies:

$$\ln(y_{jst}) = \alpha + \beta_1 \cdot Adopt_{st} + \beta_2 \cdot Adopt_{st} \times Low_j + \beta_3 \cdot Adopt_{st} \times High_j + \gamma_j + \delta_t + \pi_s + \pi_s \times t + \epsilon_{jst} \tag{1}$$

where, y_{jst} is occupation j employment (in state s) per state s population in month-year t.

$Adopt_{st}$ is the dummy indicating whether the state is currently adopting the law. This dummy is set to one starting the month right after the initial adoption. Each of the three at-will exceptions is analyzed separately. $Low_j$and $High_j$ are the dummies denoting whether the occupation is of the low-investment and high-investment occupation groups. γ_j's, δ_t's, and π_s's are occupational fixed effects, time fixed effects, and state fixed effects, respectively. $\pi_s \times t$'s are the state-specific time trends. We will also add occupation-specific time trends ($\gamma_j \times t$) in some of our specifications. The state dummies, time dummies, and the state-specific time trends should capture the state characteristics that change over time that may be correlated with the decision to adopt the law by the state (address the endogeneity issue).

The question we look to answer from this regression is whether or not the law change affects employment of each occupation (per state population). The law can affect this variable through a number of routes. For example, some of the changes will arise from workers shifting in and out of employment. Some of the changes will arise from workers shifting from one set of occupations to another. Thus, even if the overall effect of the law is negative, it may still have a positive effect on a set of occupations that expand employment. It is sensible to argue that the composition of state population may change over time and this may be correlated with the law change. We address this by including observable state-level characteristics in our model. These observable characteristics are fraction of male workers, fraction of black workers, fraction of workers in each age group (18-35, and 36-55), fraction of married workers, fraction of unionized workers, and fraction of workers in each education group (high school graduates, some college, and college education or higher). In this case the model becomes:

$$\ln(y_{jst}) = \alpha + \eta' x_{st} + \beta_1 \cdot Adopt_{st} + \beta_2 \cdot Adopt_{st} \times Low_j + \beta_3 \cdot Adopt_{st} \times High_j + \gamma_j + \delta_t + \pi_s + \pi_s \times t + \epsilon_{jst} \quad (2)$$

where x_{st} is the vector of state's characteristics.

The effects of the laws on wages are estimated using the following model:

$$\ln(w_{jst}) = \alpha + \eta' x_{st} + \beta_1 \cdot Adopt_{st} + \beta_2 \cdot Adopt_{st} \times Low_j + \beta_3 \cdot Adopt_{st} \times High_j + \gamma_j + \delta_t + \pi_s + \pi_s \times t + \epsilon_{jst} \quad (3)$$

where, w_{jst} is the average real wage for each occupation in state s and year t. x_{st} is the vector of the characteristics of workers in state s (at time t). We start by estimating the first set of our wage regression without the controls. Then, in the second set, we do include them. It was quite unambiguous in the employment regression why the controls x_{st} should be at the state level. However, it is quite arguable whether we should use the occupation-state level controls or the state-level controls in our wage regression. Our argument against the occupation-state level controls is that, in the CPS the occupation-state-year cells are quite small (small number of observations), and hence there is a great deal of measurement error associated with using these controls at that level. Our argument for the state-level controls is that, the adoption of the law should be more likely to be associated with the population characteristics in the state rather than the workers' characteristics in each occupation. In other words, if the legislators did look at the environment in deciding to adopt the law, we think this environment would be the state-level environment and not the occupation-state-level one since the law they are deciding on will affect all workers in the state not just those in some particular occupations.

We weigh the employment regression by (the square root of) the number of observations that belong to each occupation-state cell. For the wage regression, we use (the square root of) the number of observations that belong to each occupation-state cell that have valid wage information as the weight. The weighing of the regressions is done to achieve some efficiency gain due to possible heteroskedasticity. As observed by Bertrand, Duflo, and Mullainathan (2004), it is important to adjust the standard errors to take into account possible correlation over time and within state or the data series. Accordingly, we use Huber-White standard error estimation method clustered by state to allow such possibilities.

5 Results

5.1 Implied Contract Exception to Employment at Will

Table 3 reports the results of the effect of the implied contract exception upon employment and wages using each of the four criteria of investment. We include state fixed effects, time fixed effects, occupation fixed effects, and state-specific time trends in all models. In some of the models, we also include the occupation-specific time trends. For low-investment workers, the total effect (Adopt + Adopt x Low) is significantly negative with a point estimate ranging from 5.7% to 7.4%. The significance of the estimate is robust to the inclusion of the occupation-specific time trends when any kind of trianing criterion is used. Conversely, there is a positive and significant impact of the law on the employment of high-investment workers (Adopt + Adopt x High) with a magnitude ranging from 5.4% to 7.7%. Under school training criterion, the estimate remains significant once the occupation-specific time trends are included. The impact of the law on aggregate employment is almost zero since the positive and the negative impacts on different occupation groups seem to be offsetting. Observing closely at the estimates under informal training criterion, we can see that one cannot distinguish the impact of the law on the low-invesment and the high-investment workers since they both are insignificant. However, for the medium-investment group the impact on employment is negative (4.1% to 4.3%). One reason for explaining the unpromising results from the informal training criterion columns is that workers may not have been made clear what informal training mean when asked the question. For example, some workers may regard learning-by-doing as a kind of informal training, but some may not. Such inconsistencies may cause the calculation of fraction of workers reported having received informal training to be spurious. Table 3B reports the impact upon wages. The effects seem to be zero. This suggest that, at least for the high-investment workers, the law change may have an overall positive effect on their welfare (positive employment effect, zero wage effect).

In table 4 we explore the consequence of adding addition state level controls. We find that this has a small impact on the R^2, and slightly decreases the significance of the parameters of interest, though the point estimates do not change. These results are likely due to the fact that some of the state-characteristic controls may be slightly correlated with the adoption of the law.

To get a further sense of the economic significance of the law changes we investigate this point by separating the data into highly populated and sparsely populated labor markets. We define a highly populated labor market by the area belonging to the Standard Metropolitan Statistical Area (SMSA) with population one million or more for our 1983 and 1984 data and the area 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 3.

We would expect a larger negative effect, and in fact we find the point estimate to be three times larger in the large market relative to the small market. The results are reported in tables 5 and 6. The negative impacts of the law on employment of low-investment workers are highly significant in the highly populated area (Table 5A). They however are not significant in the sparsely populated area (Table 6A). For the high investment occupations, there is little evidence of positive employment impact in the highly populated area but no significant impact in the sparsely populated area. Hence, this suggests that the positive effect of the law change on employment is not as strong as the negative effect, particularly for the larger labor market. As for wages, we find no effects of the law in the dense area (Table 5B) but find little evidence of positive impact in the low density area surprisingly for the low-investment workers.

5.2 Good Faith Exception to Employment at Will

The results of the effect of the good faith exception are reported in table 7. As we saw in figures 1 and 2, the number of states introducing this law are quite small. Hence, the effect is being estimated from changes of law in about 10 states. Moreover, the legal analysis suggests that the effect is rather narrow. On the positive side, the law is clearer relative to the implied contract exception - it prohibits opportunistic behavior on the part of the employer. We can see that the adoption of the law has no effect upon wages, but a negative effect on the low investment group and positive effect on the high investment group. The impact of the law on the employment of low-investment workers ranges from 8.6% to 10.1%. The positive employment impact on high-investment workers ranges from 8.7% to 13.4%. The estimated effects of the laws once we include state-level controls are reported in table 8. The point estimates change very little and the significance of the estimates remain unchanged. These patterns of the results are similar with the patterns found in the case of the implied contract exception. However, it is quite surprising that we get quite large and highly significant estimates for good faith.

6 Conclusion

The main message of this paper is that it is overly simplistic to view employment protection legislation as simply adding a cost to worker dismissals, as is typically assumed in the literature. The real issue is how to achieve an optimal structure of the employment contract, and whether legal intervention into private agreements can enhance or reduce economic performance. If all agents are rational and contracts are complete, then WDL should have a minimal impact upon the labor market. Early work with US data, particularly Autor, Donohue, and Schwab (2006) has found that changes in US employment law has had a significant negative effect.

In contrast, we find that it depends. There is a great deal of heterogeneity in employment relationships. Just as not all employees are of high quality, neither are all employers. Both may benefit from clearly understanding the rules regulating their relationship. We find that in occupations characterized by high investment into worker human capital that both the implied contract and good faith exceptions to employment at will increase employment. This is consistent with the intuition that long terms contracts are needed in these cases.

The negative impact of the law on occupations with low investment is consistent with earlier literature. Botero, Djankov, La Porta, Lopez-de Silanes, and Shleifer (2004) study the impact of labor regulation upon employment in 85 countries. They find that in countries that places more dependence upon formal arrangements have lower employment. This suggests that there are efficiency advantages to using informal employment contracts that do not depend upon formal contingencies, such as employment at will. Bernheim and Whinston (1998) argue that leaving terms open can enhance the efficiency of economic relationships. Scott (2003) studies a number of contract cases and concludes that indeed parties in practice leave important terms vague. Our results suggest that when there is less at stake, then parties may perform less binding contractual obligations - and the reverse when the relationship requires more protection. Our understanding of these issues is very incomplete, and we hope to explore these issues further.

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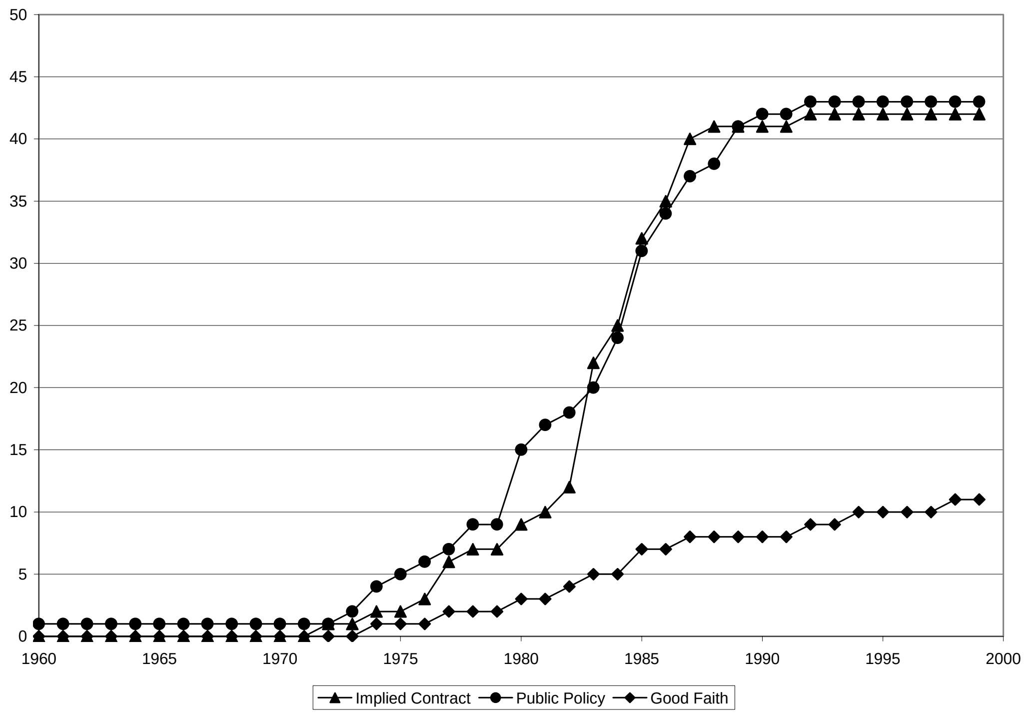
Figures and Tables

Figure 1: Number of States Adopting at-will Exceptions



Source: Illustrated from Autor, Donohue III, and Schwab (2005)'s Legal Appendix

Figure 2: Pattern of Adoption During 1983-1994

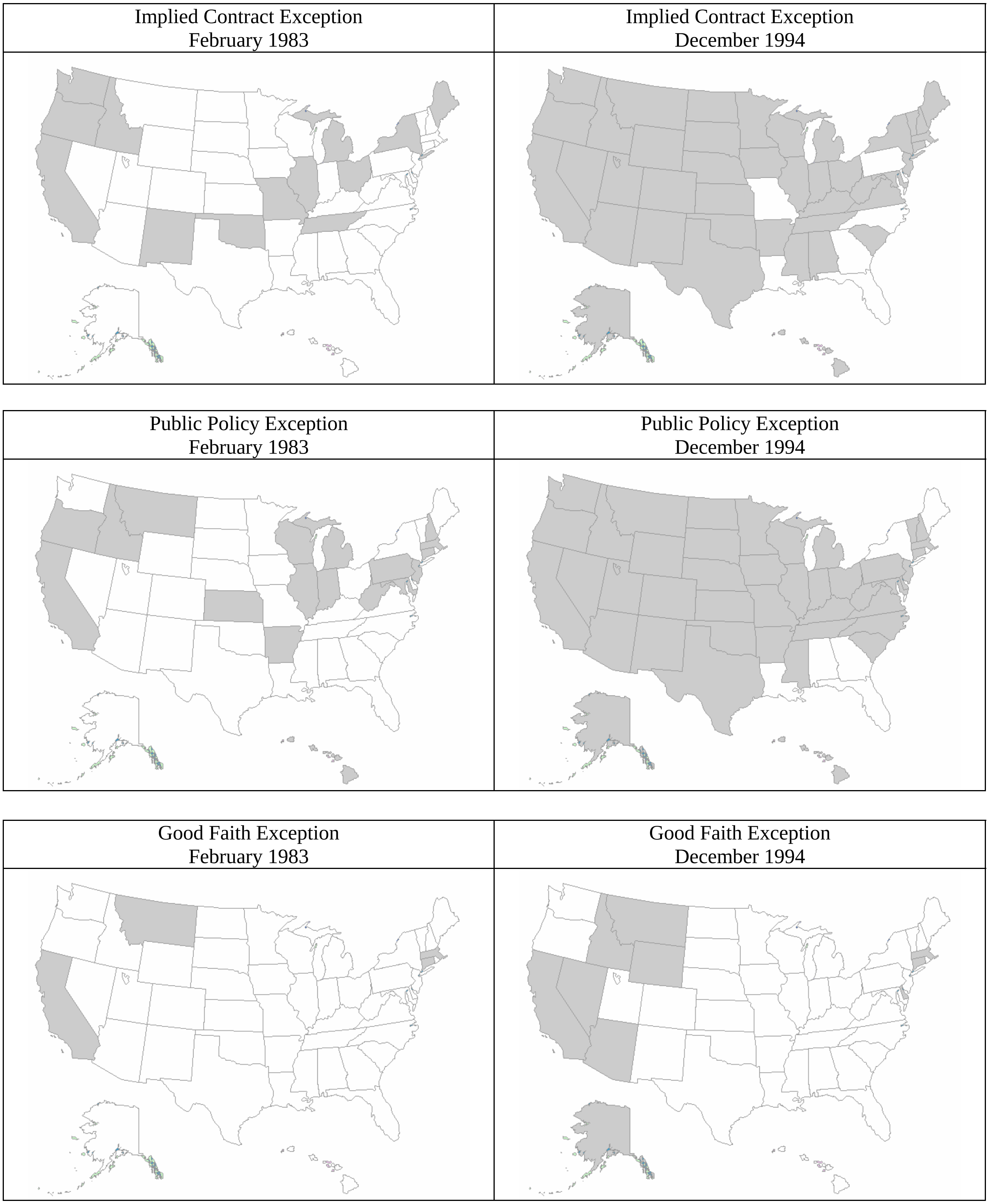


Figure 3A: States that contain "Highly populated area"
SMSA with population 1M+ (1983-1984)

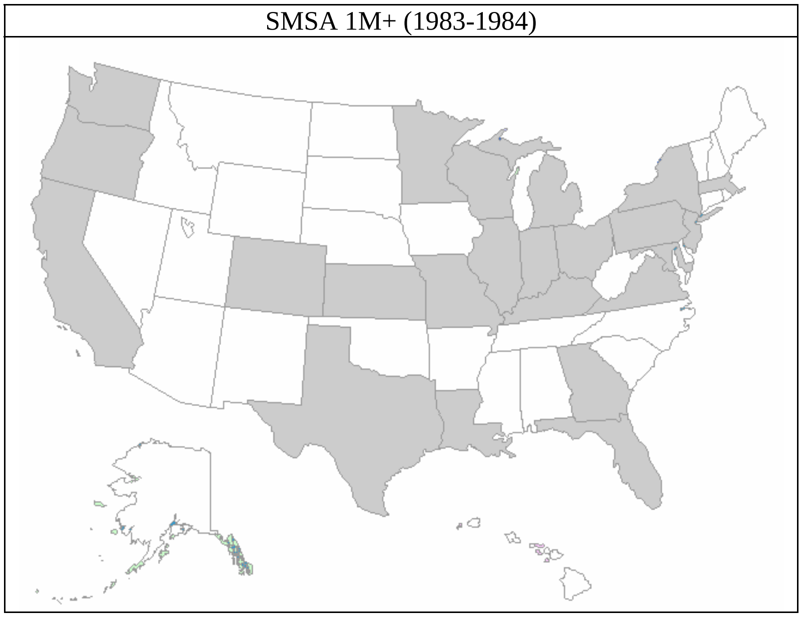


Figure 3B: States that contain "Highly populated area"
MSA with population 1M+ (1985-1994)

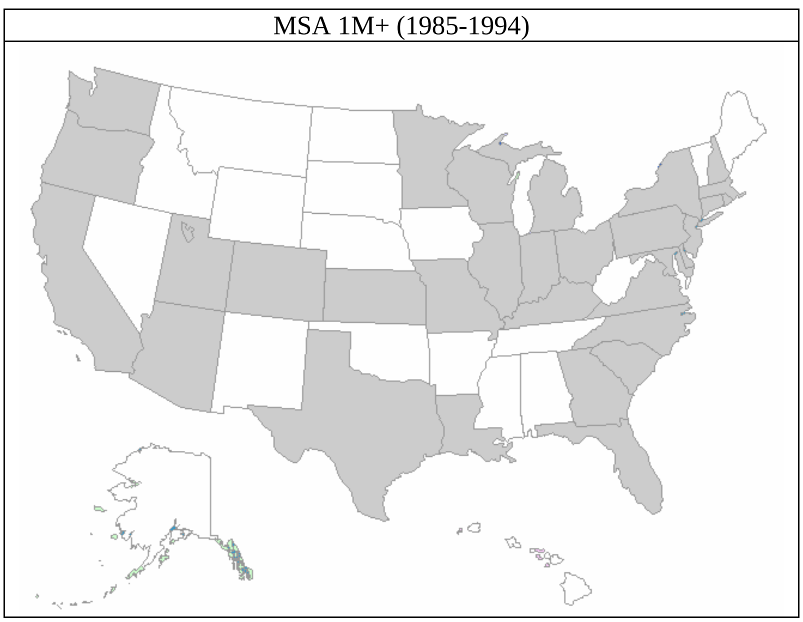


Table 1: Adoption Dates

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 III, and Schwab (2005)'s Legal Appendix

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

Occupational Code	Occupation	Fraction of workers received any kind of training after obtaining current job	Low vs High
27	Private Household Service Occupations	0.0544938	Low = 1 High = 0
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	Low = 0 High = 0
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	Low = 0 High = 1
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

Occupational Code	Occupation	Fraction of workers received (employer paid) school training after obtaining current job	Low vs High
25	Mail and Message Distributing	0	Low = 1 High = 0
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	Low = 0 High = 0
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	Low = 0 High = 1
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

Occupational Code	Occupation	Fraction of workers received formal company training after obtaining current job	Low vs High
43	Farm Operators and Managers	0.0175515	Low = 1 High = 0
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	Low = 0 High = 0
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	Low = 0 High = 1
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

Occupational Code	Occupation	Fraction of workers received informal on-the-job training after obtaining current job	Low vs High
20	Sales Related Occupations	0	Low = 1 High = 0
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	Low = 0 High = 0
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	Low = 0 High = 1
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 3A: Implied Contract Exception (All Area) [Dep Var: LN(emp/pop)]
No Controls for Characteristics

	Any kind of training		School training		Formal training		Informal training	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Adopt(IC)	**0.00535**	**0.00104**	**-0.02354***	**-0.02347***	**0.00652**	**-0.00394**	**-0.04114****	**-0.04388****
	[0.43016]	**[0.07674]**	**[1.86286]**	**[1.80159]**	**[0.46895]**	**[0.26727]**	**[2.21933]**	**[2.27169]**
Adopt(IC)xLow(Any training)	-0.07973**	-0.06068						
	[2.13740]	[1.47202]						
Adopt(IC)xHigh(Any training)	0.06766***	0.05119**						
	[3.26420]	[2.13886]						
Adopt(IC)xLow(School training)			-0.03862	-0.02328				
			[1.00361]	[0.56068]				
Adopt(IC)xHigh(School training)			0.10078***	0.07789***				
			[4.91252]	[3.09599]				
Adopt(IC)xLow(Formal company training)					-0.06358	-0.03735		
					[1.56054]	[0.84456]		
Adopt(IC)xHigh(Formal company trianing)					0.02223*	0.02627**		
					[1.78016]	[2.03741]		
Adopt(IC)xLow(Informal training)							0.04988	0.06567*
							[1.33451]	[1.65962]
Adopt(IC)xHigh(Informal training)							0.05057*	0.04294
							[1.86361]	[1.46462]
Constant	-5.61870***	-5.60513***	-5.62213***	-5.60703***	-5.58632***	-5.58351***	-5.57222***	-5.56627***
	[73.98093]	[72.20870]	[75.13135]	[72.86204]	[76.07793]	[75.12971]	[75.15224]	[73.65661]
State-specific time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation-specific time trends	No	Yes	No	Yes	No	Yes	No	Yes
Observations	313951	313951	313951	313951	313951	313951	313951	313951
R-squared	0.82718	0.83233	0.82712	0.83226	0.82648	0.83191	0.82627	0.83199
T test: Adopt+AdoptxLow=0	**-0.07438*****	**-0.05964***	**-0.06216****	**-0.04675**	**-0.05706****	**-0.04128**	**0.00874**	**0.02179**
T-statistic_1	**[2.64950]**	**[1.94625]**	**[2.05280]**	**[1.42080]**	**[1.96093]**	**[1.31143]**	**[0.36236]**	**[0.85054]**
T test: Adopt+AdoptxHigh=0	**0.07301****	**0.05223**	**0.07724*****	**0.05442***	**0.02875**	**0.02233**	**0.00942**	**-0.00094**
T-statistic_2	**[2.53833]**	**[1.61429]**	**[2.95978]**	**[1.80343]**	**[1.28665]**	**[0.92230]**	**[0.58354]**	**[0.05363]**
F test: Adopt=AdoptxLow=AdoptxHigh=0	4.25001	2.45841	11.63090	5.02955	2.52636	3.44125	1.97075	2.10337
Prob > F	0.00521	0.06085	0.00000	0.00174	0.05556	0.01601	0.11596	0.09746

Robust (absolute value of) t statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3B: Implied Contract Exception (All Area) [Dep Var: LN(avg wage)]
No Controls for Characteristics

	Any kind of training		School training		Formal training		Informal training	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Adopt(IC)	**-0.00754**	**-0.00668**	**0.00275**	**0.00249**	**0.00383**	**0.00337**	**0.00561**	**0.01315****
	[1.37339]	**[1.17539]**	**[0.51964]**	**[0.47074]**	**[0.76083]**	**[0.68130]**	**[0.81647]**	**[2.00720]**
Adopt(IC)xLow(Any training)	0.01522	0.01969*						
	[1.45572]	[1.91552]						
Adopt(IC)xHigh(Any training)	0.01935**	0.00665						
	[2.22208]	[0.82582]						
Adopt(IC)xLow(School training)			-0.00074	0.00279				
			[0.07858]	[0.30423]				
Adopt(IC)xHigh(School training)			-0.00072	-0.00535				
			[0.10189]	[0.72764]				
Adopt(IC)xLow(Formal company training)					-0.00314	-0.00035		
					[0.36727]	[0.04256]		
Adopt(IC)xHigh(Formal company trianing)					-0.00197	-0.00557		
					[0.31164]	[0.87131]		
Adopt(IC)xLow(Informal training)							-0.00411	-0.02103*
							[0.32271]	[1.69606]
Adopt(IC)xHigh(Informal training)							-0.00695	-0.01685**
							[0.80748]	[2.21681]
Constant	2.35417***	2.36111***	2.36138***	2.36337***	2.36153***	2.36296***	2.36376***	2.36394***
	[160.18939]	[164.20559]	[172.65647]	[173.16259]	[164.43496]	[162.39446]	[162.25399]	[158.85125]
State-specific time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation-specific time trends	No	Yes	No	Yes	No	Yes	No	Yes
Observations	26568	26568	26568	26568	26568	26568	26568	26568
R-squared	0.93330	0.93783	0.93318	0.93772	0.93318	0.93772	0.93319	0.93784
T test: Adopt+AdoptxLow=0	**0.00768**	**0.01301***	**0.00201**	**0.00528**	**0.00068**	**0.00302**	**0.00150**	**-0.00788**
T-statistic_1	**[0.93830]**	**[1.65574]**	**[0.25421]**	**[0.68029]**	**[0.10250]**	**[0.45967]**	**[0.18068]**	**[0.93547]**
T test: Adopt+AdoptxHigh=0	**0.01181**	**-0.00003**	**0.00203**	**-0.00285**	**0.00186**	**-0.00220**	**-0.00134**	**-0.00370**
T-statistic_2	**[1.21744]**	**[0.00365]**	**[0.26843]**	**[0.37783]**	**[0.27443]**	**[0.32563]**	**[0.23438]**	**[0.65751]**
F test: Adopt=AdoptxLow=AdoptxHigh=0	3.60347	1.76889	0.12482	0.25770	0.20190	0.39670	0.42592	1.78317
Prob > F	0.01281	0.15070	0.94547	0.85589	0.89513	0.75538	0.73442	0.14795

Robust (absolute value of) t statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4A: Implied Contract Exception (All Area) [Dep Var: LN(emp/pop)]
Controls for Characteristics are at the State Level

	Any kind of training		School training		Formal training		Informal training	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Adopt(IC)	**0.00570**	**0.00137**	**-0.02320***	**-0.02313***	**0.00685**	**-0.00363**	**-0.04077****	**-0.04351****
	[0.43678]	**[0.09704]**	**[1.78743]**	**[1.73305]**	**[0.47246]**	**[0.23561]**	**[2.25559]**	**[2.30468]**
Adopt(IC)xLow(Any training)	-0.07969**	-0.06063						
	[2.13693]	[1.47096]						
Adopt(IC)xHigh(Any training)	0.06761***	0.05112**						
	[3.26021]	[2.13444]						
Adopt(IC)xLow(School training)			-0.03855	-0.02321				
			[1.00196]	[0.55902]				
Adopt(IC)xHigh(School training)			0.10074***	0.07783***				
			[4.90928]	[3.09118]				
Adopt(IC)xLow(Formal company training)					-0.06350	-0.03725		
					[1.55862]	[0.84234]		
Adopt(IC)xHigh(Formal company trianing)					0.02224*	0.02629**		
					[1.78014]	[2.03715]		
Adopt(IC)xLow(Informal training)							0.04992	0.06570*
							[1.33577]	[1.66045]
Adopt(IC)xHigh(Informal training)							0.05054*	0.04292
							[1.86233]	[1.46357]
%male	0.32971***	0.32443***	0.33211***	0.32622***	0.33060***	0.32514***	0.32984***	0.32437***
	[4.38461]	[4.39036]	[4.40422]	[4.40098]	[4.37278]	[4.38688]	[4.37351]	[4.39525]
%black	-0.22687***	-0.22174***	-0.22653***	-0.22116***	-0.22644***	-0.22091***	-0.22407***	-0.22025***
	[3.00164]	[2.98137]	[3.01251]	[2.98692]	[3.00315]	[2.97694]	[2.97710]	[2.98348]
%age18-35	0.73748***	0.73546***	0.73761***	0.73595***	0.73928***	0.73730***	0.74370***	0.74062***
	[13.03443]	[13.53521]	[13.08278]	[13.61304]	[13.08866]	[13.60890]	[13.25375]	[13.74000]
%age36-55	0.60308***	0.60251***	0.60235***	0.60221***	0.60149***	0.60194***	0.60171***	0.60133***
	[9.38780]	[9.71421]	[9.37090]	[9.70739]	[9.31117]	[9.67636]	[9.32827]	[9.69236]
%married	0.00078	-0.00309	0.00188	-0.00221	0.00053	-0.00376	-0.00098	-0.00505
	[0.01800]	[0.07295]	[0.04340]	[0.05249]	[0.01223]	[0.08970]	[0.02285]	[0.12055]
%union	0.37011***	0.36946***	0.37239***	0.37091***	0.37177***	0.37061***	0.36995***	0.36783***
	[4.62597]	[4.64241]	[4.67846]	[4.67792]	[4.63065]	[4.64282]	[4.58536]	[4.59798]
%high school education	0.20470***	0.21269***	0.20165***	0.21008***	0.20349***	0.21220***	0.19519***	0.20425***
	[3.61353]	[3.79262]	[3.54391]	[3.73186]	[3.57888]	[3.77465]	[3.37081]	[3.57555]
%some college education	0.28295***	0.30051***	0.28110***	0.29882***	0.28257***	0.30116***	0.28302***	0.30204***
	[3.83469]	[4.17556]	[3.78216]	[4.12700]	[3.80206]	[4.16539]	[3.80784]	[4.18614]
%college education and higher	0.26173***	0.26790***	0.25956***	0.26620***	0.26148***	0.26845***	0.26130***	0.26839***
	[3.47099]	[3.58846]	[3.43442]	[3.55843]	[3.45606]	[3.59285]	[3.48567]	[3.63900]
Constant	-6.41824***	-6.40645***	-6.42137***	-6.40815***	-6.38566***	-6.38526***	-6.36838***	-6.36454***
	[69.26006]	[69.08703]	[69.62243]	[69.15183]	[70.03426]	[70.34947]	[69.11082]	[69.08264]
State-specific time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation-specific time trends	No	Yes	No	Yes	No	Yes	No	Yes
Observations	313951	313951	313951	313951	313951	313951	313951	313951
R-squared	0.82738	0.83253	0.82731	0.83246	0.82668	0.83211	0.82647	0.83219
T test: Adopt+AdoptxLow=0	**-0.07399*****	**-0.05925****	**-0.06175****	**-0.04634**	**-0.05665****	**-0.04088**	**0.00915**	**0.02219**
T-statistic_1	**[2.71776]**	**[1.99491]**	**[2.09030]**	**[1.44493]**	**[1.99789]**	**[1.33443]**	**[0.38744]**	**[0.88705]**
T test: Adopt+AdoptxHigh=0	**0.07330****	**0.05250**	**0.07754*****	**0.05469**	**0.02909**	**0.02266**	**0.00978**	**-0.00059**
T-statistic_2	**[2.47819]**	**[1.57905]**	**[2.89194]**	**[1.76522]**	**[1.27372]**	**[0.91345]**	**[0.57251]**	**[0.03186]**
F test: Adopt=AdoptxLow=AdoptxHigh=0	4.55160	2.76496	11.67957	5.28029	2.72460	3.57044	2.21916	2.24354
Prob > F	0.00342	0.04030	0.00000	0.00122	0.04255	0.01339	0.08366	0.08100

Robust (absolute value of) t statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4B: Implied Contract Exception (All Area) [Dep Var: LN(avg wage)]
Controls for Characteristics are at the State Level

	Any kind of training		School training		Formal training		Informal training	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Adopt(IC)	**-0.00659**	**-0.00569**	**0.00370**	**0.00347**	**0.00478**	**0.00435**	**0.00655**	**0.01411****
	[1.27871]	**[1.07175]**	**[0.75539]**	**[0.70740]**	**[0.95594]**	**[0.87792]**	**[1.00396]**	**[2.31637]**
Adopt(IC)xLow(Any training)	0.01526	0.01973*						
	[1.45936]	[1.91968]						
Adopt(IC)xHigh(Any training)	0.01938**	0.00667						
	[2.22413]	[0.82756]						
Adopt(IC)xLow(School training)			-0.00069	0.00285				
			[0.07330]	[0.31072]				
Adopt(IC)xHigh(School training)			-0.00070	-0.00534				
			[0.09866]	[0.72636]				
Adopt(IC)xLow(Formal company training)					-0.00310	-0.00029		
					[0.36300]	[0.03576]		
Adopt(IC)xHigh(Formal company trianing)					-0.00197	-0.00558		
					[0.31198]	[0.87278]		
Adopt(IC)xLow(Informal training)							-0.00401	-0.02093*
							[0.31385]	[1.68427]
Adopt(IC)xHigh(Informal training)							-0.00695	-0.01685**
							[0.80713]	[2.21361]
%male	0.15551	0.15328	0.15506	0.15218	0.15484	0.15195	0.15499	0.15126
	[0.60468]	[0.58823]	[0.60307]	[0.58430]	[0.60228]	[0.58340]	[0.60249]	[0.57970]
%black	-0.17786	-0.17573	-0.17819	-0.17583	-0.17818	-0.17549	-0.17804	-0.17393
	[1.39245]	[1.33651]	[1.39443]	[1.33868]	[1.39439]	[1.33720]	[1.39120]	[1.32183]
%age18-35	0.34018**	0.34830**	0.34024**	0.34817**	0.34019**	0.34814**	0.34020**	0.34776**
	[2.35136]	[2.39652]	[2.35325]	[2.39902]	[2.35360]	[2.40022]	[2.35081]	[2.39135]
%age36-55	0.10070	0.11247	0.10092	0.11314	0.10091	0.11353	0.10079	0.11309
	[0.69177]	[0.76840]	[0.69488]	[0.77551]	[0.69510]	[0.77923]	[0.69346]	[0.77579]
%married	0.10265	0.10131	0.10243	0.10197	0.10260	0.10242	0.10201	0.10235
	[1.18333]	[1.15453]	[1.17697]	[1.16015]	[1.17887]	[1.16569]	[1.17110]	[1.16574]
%union	0.29769	0.29223	0.29765	0.29283	0.29782	0.29308	0.29790	0.29632
	[1.50923]	[1.46908]	[1.51021]	[1.47471]	[1.51140]	[1.47656]	[1.51312]	[1.49405]
%high school education	-0.18849*	-0.19119*	-0.18740*	-0.19015*	-0.18737*	-0.19048*	-0.18708*	-0.18649*
	[1.71139]	[1.71314]	[1.70122]	[1.70424]	[1.70314]	[1.71092]	[1.68850]	[1.66688]
%some college education	0.11610	0.12279	0.11536	0.12250	0.11515	0.12185	0.11545	0.12154
	[0.85986]	[0.90986]	[0.85426]	[0.90708]	[0.85276]	[0.90283]	[0.85523]	[0.90141]
%college education and higher	0.30107**	0.31305**	0.30109**	0.31356**	0.30112**	0.31348**	0.30145**	0.31541**
	[2.09327]	[2.15926]	[2.08868]	[2.15534]	[2.08701]	[2.15201]	[2.08821]	[2.15505]
Constant	2.04859***	2.04913***	2.05574***	2.05080***	2.05593***	2.05036***	2.05826***	2.04976***
	[14.41759]	[14.22176]	[14.40337]	[14.19104]	[14.36845]	[14.16499]	[14.36736]	[14.14595]
State-specific time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation-specific time trends	No	Yes	No	Yes	No	Yes	No	Yes
Observations	26568	26568	26568	26568	26568	26568	26568	26568
R-squared	0.93346	0.93800	0.93334	0.93789	0.93335	0.93789	0.93336	0.93801
T test: Adopt+AdoptxLow=0	**0.00867**	**0.01404***	**0.00300**	**0.00632**	**0.00168**	**0.00406**	**0.00255**	**-0.00682**
T-statistic_1	**[1.11594]**	**[1.91332]**	**[0.40967]**	**[0.88945]**	**[0.27538]**	**[0.68748]**	**[0.30448]**	**[0.79615]**
T test: Adopt+AdoptxHigh=0	**0.01279**	**0.00097**	**0.00300**	**-0.00187**	**0.00281**	**-0.00122**	**-0.00040**	**-0.00274**
T-statistic_2	**[1.30971]**	**[0.10903]**	**[0.38541]**	**[0.23888]**	**[0.43771]**	**[0.19176]**	**[0.07673]**	**[0.54058]**
F test: Adopt=AdoptxLow=AdoptxHigh=0	3.76303	1.97960	0.33530	0.50158	0.37731	0.57068	0.61082	2.00221
Prob > F	0.01027	0.11465	0.79983	0.68118	0.76937	0.63427	0.60790	0.11132

Robust (absolute value of) t statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5A: Implied Contract Exception (Highly Populated Area: Population > 1M) [Dep Var: LN(emp/pop)]
Controls for Characteristics are at the State Level

	Any kind of training		School training		Formal training		Informal training	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Adopt(IC)	**-0.02554***	**-0.02315***	**-0.05258*****	**-0.04804*****	**-0.01129**	**-0.01342**	**-0.02513**	**-0.02408**
	[1.91191]	**[1.73856]**	**[3.27505]**	**[2.95142]**	**[0.66716]**	**[0.79616]**	**[1.23664]**	**[1.19491]**
Adopt(IC)xLow(Any training)	-0.06329**	-0.05926*						
	[2.04305]	[1.84474]						
Adopt(IC)xHigh(Any training)	0.06590***	0.05339*						
	[2.78065]	[1.93997]						
Adopt(IC)xLow(School training)			-0.02852	-0.02698				
			[0.90431]	[0.82969]				
Adopt(IC)xHigh(School training)			0.10377***	0.08923***				
			[4.04254]	[2.95553]				
Adopt(IC)xLow(Formal company training)					-0.06684*	-0.05826		
					[1.86388]	[1.56054]		
Adopt(IC)xHigh(Formal company trianing)					0.00678	0.00769		
					[0.24659]	[0.27000]		
Adopt(IC)xLow(Informal training)							-0.02873	-0.02729
							[0.92350]	[0.83562]
Adopt(IC)xHigh(Informal training)							0.00953	0.00689
							[0.32697]	[0.23051]
%male	0.28165***	0.28587***	0.28548***	0.28899***	0.28381***	0.28747***	0.28082***	0.28475***
	[3.26308]	[3.40359]	[3.33225]	[3.46319]	[3.27709]	[3.41731]	[3.24621]	[3.38652]
%black	-0.31895***	-0.32447***	-0.32387***	-0.32853***	-0.31800***	-0.32424***	-0.31650***	-0.32343***
	[2.58815]	[2.57750]	[2.62046]	[2.60083]	[2.62021]	[2.60131]	[2.65435]	[2.62892]
%age18-35	0.71709***	0.71549***	0.71676***	0.71538***	0.71700***	0.71562***	0.71986***	0.71824***
	[10.84073]	[11.11470]	[10.87913]	[11.15624]	[10.88477]	[11.17025]	[10.83315]	[11.09967]
%age36-55	0.58595***	0.58989***	0.58639***	0.59021***	0.58835***	0.59213***	0.59123***	0.59455***
	[9.87414]	[10.17183]	[9.84572]	[10.11942]	[9.86765]	[10.13407]	[9.76306]	[10.01007]
%married	-0.09406*	-0.09917*	-0.09267*	-0.09803*	-0.09573*	-0.10064*	-0.09569*	-0.10067*
	[1.76735]	[1.88233]	[1.73508]	[1.85591]	[1.81197]	[1.91877]	[1.82500]	[1.93263]
%union	0.24929**	0.24590**	0.25124**	0.24734**	0.24564**	0.24276**	0.24210**	0.23971**
	[2.50417]	[2.47291]	[2.53877]	[2.50090]	[2.46138]	[2.43416]	[2.42529]	[2.40299]
%high school education	0.15553**	0.16571**	0.15485**	0.16507**	0.15575**	0.16618**	0.15325**	0.16460**
	[1.99026]	[2.11636]	[1.96822]	[2.09427]	[1.99959]	[2.12531]	[1.96086]	[2.09537]
%some college education	0.10437	0.11575	0.10490	0.11586	0.10160	0.11356	0.09693	0.10997
	[1.15601]	[1.28463]	[1.15222]	[1.27646]	[1.12853]	[1.26366]	[1.07225]	[1.21760]
%college education and higher	0.20577**	0.21377**	0.20483**	0.21282**	0.20078**	0.20987**	0.19403*	0.20457*
	[2.00142]	[2.03583]	[1.97325]	[2.00768]	[1.97147]	[2.01194]	[1.88367]	[1.93763]
Constant	-6.08632***	-6.08730***	-6.09654***	-6.09717***	-6.04894***	-6.05759***	-6.03706***	-6.04623***
	[37.84481]	[37.89739]	[37.68436]	[37.69256]	[38.18669]	[38.43098]	[37.00888]	[37.21423]
State-specific time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation-specific time trends	No	Yes	No	Yes	No	Yes	No	Yes
Observations	143729	143729	143729	143729	143729	143729	143729	143729
R-squared	0.87727	0.88100	0.87743	0.88112	0.87689	0.88072	0.87666	0.88055
T test: Adopt+AdoptxLow=0	**-0.08883*****	**-0.08242*****	**-0.08109*****	**-0.07502*****	**-0.07813*****	**-0.07168****	**-0.05386*****	**-0.05136****
T-statistic_1	**[3.30858]**	**[2.93278]**	**[2.98896]**	**[2.62831]**	**[2.84007]**	**[2.48918]**	**[2.79914]**	**[2.46978]**
T test: Adopt+AdoptxHigh=0	**0.04036**	**0.03024**	**0.05120****	**0.04119**	**-0.00451**	**-0.00573**	**-0.01560**	**-0.01719**
T-statistic_2	**[1.36589]**	**[0.95346]**	**[1.97886]**	**[1.46067]**	**[0.15859]**	**[0.19836]**	**[0.80308]**	**[0.87101]**
F test: Adopt=AdoptxLow=AdoptxHigh=0	5.72086	4.20167	7.71808	5.21029	3.71774	3.24848	3.97537	3.28681
Prob > F	0.00065	0.00557	0.00004	0.00135	0.01093	0.02086	0.00764	0.01979

Robust (absolute value of) t statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5B: Implied Contract Exception (Highly Populated Area: Population > 1M) [Dep Var: LN(avg wage)]
Controls for Characteristics are at the State Level

	Any kind of training		School training		Formal training		Informal training	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Adopt(IC)	**-0.00726**	**-0.00737**	**0.00026**	**-0.00078**	**0.00172**	**0.00074**	**-0.00010**	**0.00427**
	[1.08589]	**[1.10923]**	**[0.03407]**	**[0.10151]**	**[0.24785]**	**[0.10818]**	**[0.00963]**	**[0.43801]**
Adopt(IC)xLow(Any training)	-0.00012	0.00456						
	[0.00892]	[0.37591]						
Adopt(IC)xHigh(Any training)	0.01941*	0.01328						
	[1.76356]	[1.23023]						
Adopt(IC)xLow(School training)			-0.01702	-0.01293				
			[1.49792]	[1.18590]				
Adopt(IC)xHigh(School training)			0.00708	0.00602				
			[0.81206]	[0.65667]				
Adopt(IC)xLow(Formal company training)					-0.01421	-0.01034		
					[1.60433]	[1.28338]		
Adopt(IC)xHigh(Formal company trianing)					0.00025	-0.00120		
					[0.03338]	[0.16070]		
Adopt(IC)xLow(Informal training)							-0.00494	-0.01447
							[0.26874]	[0.76104]
Adopt(IC)xHigh(Informal training)							-0.00337	-0.01004
							[0.27924]	[0.87345]
%male	0.32675	0.32757	0.32888	0.32889	0.32946	0.32913	0.32965	0.32898
	[1.59906]	[1.59359]	[1.61003]	[1.60003]	[1.61683]	[1.60386]	[1.61848]	[1.60139]
%black	-0.20263**	-0.21893**	-0.20370**	-0.21996**	-0.20282**	-0.21947**	-0.20121**	-0.21836**
	[2.24994]	[2.41427]	[2.26239]	[2.42717]	[2.24793]	[2.41710]	[2.22507]	[2.39920]
%age18-35	0.03599	0.03454	0.03533	0.03396	0.03511	0.03398	0.03613	0.03411
	[0.30451]	[0.29160]	[0.29793]	[0.28605]	[0.29650]	[0.28642]	[0.30481]	[0.28706]
%age36-55	0.07199	0.06901	0.07211	0.06898	0.07246	0.06960	0.07323	0.06921
	[0.37846]	[0.36103]	[0.37822]	[0.36029]	[0.38087]	[0.36402]	[0.38398]	[0.36077]
%married	0.01434	0.00920	0.01304	0.00842	0.01295	0.00830	0.01287	0.00823
	[0.13922]	[0.08899]	[0.12660]	[0.08141]	[0.12575]	[0.08020]	[0.12496]	[0.07949]
%union	0.30800*	0.30358*	0.30744*	0.30397*	0.30579*	0.30243*	0.30394*	0.30122*
	[1.85500]	[1.82103]	[1.85583]	[1.82836]	[1.83954]	[1.81329]	[1.82845]	[1.80381]
%high school education	0.15191	0.17166	0.15359	0.17251	0.15307	0.17214	0.15276	0.17357
	[1.04377]	[1.18596]	[1.05247]	[1.18934]	[1.05007]	[1.18841]	[1.04162]	[1.18934]
%some college education	0.06146	0.07823	0.06300	0.07972	0.06149	0.07853	0.06045	0.07838
	[0.40662]	[0.51400]	[0.41638]	[0.52357]	[0.40617]	[0.51557]	[0.39785]	[0.51343]
%college education and higher	0.28963*	0.30561**	0.29055*	0.30737**	0.28815*	0.30517**	0.28589*	0.30486**
	[1.95081]	[2.08610]	[1.94782]	[2.08926]	[1.93329]	[2.07763]	[1.90035]	[2.05719]
Constant	2.22863***	2.22185***	2.23137***	2.22148***	2.23650***	2.22664***	2.24098***	2.23069***
	[23.12509]	[22.79486]	[22.84223]	[22.55540]	[22.57354]	[22.31679]	[22.38753]	[22.21417]
State-specific time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation-specific time trends	No	Yes	No	Yes	No	Yes	No	Yes
Observations	14902	14902	14902	14902	14902	14902	14902	14902
R-squared	0.92510	0.92956	0.92513	0.92960	0.92506	0.92955	0.92500	0.92958
T test: Adopt+AdoptxLow=0	**-0.00738**	**-0.00281**	**-0.01676**	**-0.01370**	**-0.01250**	**-0.00960**	**-0.00503**	**-0.01021**
T-statistic_1	**[0.58012]**	**[0.23436]**	**[1.52141]**	**[1.30367]**	**[1.27345]**	**[1.02669]**	**[0.37503]**	**[0.72635]**
T test: Adopt+AdoptxHigh=0	**0.01215**	**0.00591**	**0.00734**	**0.00525**	**0.00197**	**-0.00046**	**-0.00347**	**-0.00578**
T-statistic_2	**[1.10237]**	**[0.56050]**	**[0.94068]**	**[0.69143]**	**[0.25178]**	**[0.06132]**	**[0.45042]**	**[0.76147]**
F test: Adopt=AdoptxLow=AdoptxHigh=0	1.15670	0.70053	1.15664	0.87907	0.88545	0.59730	0.08244	0.32627
Prob > F	0.32470	0.55161	0.32472	0.45103	0.44772	0.61671	0.96961	0.80638

Robust (absolute value of) t statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6A: Implied Contract Exception (Sparsely Populated Area: Population < 1M) [Dep Var: LN(emp/pop)]
Controls for Characteristics are at the State Level

	Any kind of training		School training		Formal training		Informal training	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Adopt(IC)	**-0.00289**	**-0.01073**	**-0.02551****	**-0.02885*****	**-0.00539**	**-0.01765**	**-0.06079*****	**-0.06588*****
	[0.27090]	**[1.03736]**	**[2.35413]**	**[2.72281]**	**[0.43329]**	**[1.39326]**	**[2.86642]**	**[2.98654]**
Adopt(IC)xLow(Any training)	-0.03754	-0.01576						
	[1.42501]	[0.58259]						
Adopt(IC)xHigh(Any training)	0.03909	0.02905						
	[1.42648]	[0.94228]						
Adopt(IC)xLow(School training)			-0.00161	0.01668				
			[0.05378]	[0.54193]				
Adopt(IC)xHigh(School training)			0.06420**	0.04573				
			[2.36681]	[1.51911]				
Adopt(IC)xLow(Formal company training)					-0.01672	0.01145		
					[0.51304]	[0.33629]		
Adopt(IC)xHigh(Formal company trianing)					0.00065	0.00515		
					[0.03166]	[0.23037]		
Adopt(IC)xLow(Informal training)							0.11182**	0.13673***
							[2.36694]	[2.90049]
Adopt(IC)xHigh(Informal training)							0.05060**	0.03862
							[2.13904]	[1.46212]
%male	0.15502**	0.15293**	0.15544**	0.15313**	0.15402**	0.15219**	0.15304**	0.15145**
	[2.08896]	[2.04806]	[2.09495]	[2.04864]	[2.07102]	[2.03255]	[2.05971]	[2.02523]
%black	-0.07929	-0.06861	-0.07896	-0.06777	-0.07854	-0.06673	-0.07955	-0.07146
	[0.87732]	[0.76469]	[0.87470]	[0.75627]	[0.86596]	[0.74263]	[0.87648]	[0.79547]
%age18-35	0.63791***	0.63581***	0.63930***	0.63683***	0.63864***	0.63630***	0.63637***	0.63229***
	[10.66792]	[10.77756]	[10.72946]	[10.82333]	[10.71760]	[10.81869]	[10.63193]	[10.70508]
%age36-55	0.62262***	0.62582***	0.62399***	0.62717***	0.62304***	0.62679***	0.62062***	0.62287***
	[9.52091]	[9.64775]	[9.57197]	[9.68835]	[9.51753]	[9.66035]	[9.47743]	[9.59553]
%married	0.02731	0.02360	0.02668	0.02304	0.02663	0.02274	0.02537	0.02092
	[0.63784]	[0.56139]	[0.62337]	[0.54783]	[0.61866]	[0.53802]	[0.58263]	[0.48895]
%union	0.49060***	0.49016***	0.49040***	0.48990***	0.49208***	0.49069***	0.49016***	0.48782***
	[5.45354]	[5.52905]	[5.47285]	[5.53867]	[5.47954]	[5.54127]	[5.43950]	[5.48280]
%high school education	0.28464***	0.28985***	0.28301***	0.28874***	0.28508***	0.29063***	0.27978***	0.28415***
	[4.53694]	[4.66104]	[4.52779]	[4.66405]	[4.56550]	[4.70080]	[4.45941]	[4.55116]
%some college education	0.23495***	0.24551***	0.23403***	0.24531***	0.23482***	0.24663***	0.23681***	0.24749***
	[2.77321]	[2.97068]	[2.76173]	[2.96911]	[2.76270]	[2.98307]	[2.77191]	[2.97505]
%college education and higher	0.40447***	0.41322***	0.40358***	0.41305***	0.40651***	0.41609***	0.40905***	0.41736***
	[3.36535]	[3.46297]	[3.35915]	[3.46549]	[3.41018]	[3.51739]	[3.45675]	[3.55880]
Constant	-6.25174***	-6.24253***	-6.25343***	-6.24151***	-6.22144***	-6.22041***	-6.21149***	-6.20092***
	[76.43125]	[75.59526]	[78.05341]	[76.91630]	[76.01025]	[75.91525]	[75.19960]	[74.68199]
State-specific time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation-specific time trends	No	Yes	No	Yes	No	Yes	No	Yes
Observations	246148	246148	246148	246148	246148	246148	246148	246148
R-squared	0.77925	0.78328	0.77923	0.78329	0.77897	0.78319	0.77979	0.78437
T test: Adopt+AdoptxLow=0	**-0.04043****	**-0.02649**	**-0.02712**	**-0.01217**	**-0.02212**	**-0.00621**	**0.05103***	**0.07086****
T-statistic_1	**[1.99513]**	**[1.24923]**	**[1.12560]**	**[0.48454]**	**[0.95480]**	**[0.25619]**	**[1.74840]**	**[2.52007]**
T test: Adopt+AdoptxHigh=0	**0.03619**	**0.01833**	**0.03869**	**0.01689**	**-0.00475**	**-0.01250**	**-0.01018**	**-0.02726***
T-statistic_2	**[1.14278]**	**[0.51975]**	**[1.23425]**	**[0.49536]**	**[0.16928]**	**[0.41237]**	**[0.67256]**	**[1.82906]**
F test: Adopt=AdoptxLow=AdoptxHigh=0	1.80695	1.47923	4.90272	4.11258	1.15432	1.50657	2.90628	4.02886
Prob > F	0.14345	0.21792	0.00208	0.00631	0.32560	0.21054	0.03327	0.00709

Robust (absolute value of) t statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6B: Implied Contract Exception (Sparsely Populated Area: Population < 1M) [Dep Var: LN(avg wage)]
Controls for Characteristics are at the State Level

	Any kind of training		School training		Formal training		Informal training	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Adopt(IC)	**-0.01084***	**-0.01029**	**-0.00201**	**-0.00254**	**-0.00074**	**-0.00058**	**0.00764**	**0.01564*****
	[1.66238]	**[1.42919]**	**[0.36453]**	**[0.44140]**	**[0.13365]**	**[0.10068]**	**[1.18666]**	**[2.66389]**
Adopt(IC)xLow(Any training)	0.02587*	0.03109**						
	[1.88869]	[2.11136]						
Adopt(IC)xHigh(Any training)	0.01250	-0.00215						
	[1.35166]	[0.30872]						
Adopt(IC)xLow(School training)			0.01442	0.01903*				
			[1.34501]	[1.68480]				
Adopt(IC)xHigh(School training)			-0.00518	-0.01140				
			[0.55393]	[1.23854]				
Adopt(IC)xLow(Formal company training)					0.00857	0.01077		
					[0.87606]	[1.02248]		
Adopt(IC)xHigh(Formal company trianing)					-0.00182	-0.00835		
					[0.28093]	[1.30139]		
Adopt(IC)xLow(Informal training)							-0.00836	-0.02607***
							[0.73731]	[2.74725]
Adopt(IC)xHigh(Informal training)							-0.01015	-0.02039***
							[1.21747]	[2.77469]
%male	0.03773	0.03122	0.03711	0.03141	0.03907	0.03410	0.04004	0.03524
	[0.22960]	[0.18912]	[0.22533]	[0.18991]	[0.23761]	[0.20666]	[0.24371]	[0.21336]
%black	-0.14626	-0.13445	-0.14685	-0.13527	-0.14634	-0.13459	-0.14596	-0.13238
	[1.30473]	[1.17867]	[1.31037]	[1.18754]	[1.30790]	[1.18257]	[1.30862]	[1.16683]
%age18-35	0.11231	0.11138	0.11211	0.11050	0.11224	0.11071	0.11275	0.11233
	[1.18349]	[1.16911]	[1.18457]	[1.16310]	[1.18622]	[1.16626]	[1.18944]	[1.17757]
%age36-55	0.14028	0.14159	0.14017	0.14056	0.14009	0.14055	0.14003	0.14141
	[1.37035]	[1.37677]	[1.36812]	[1.36468]	[1.36608]	[1.36343]	[1.36331]	[1.36725]
%married	0.18852**	0.18777**	0.18915**	0.18894**	0.18951**	0.18931**	0.18916**	0.18888**
	[2.35107]	[2.33099]	[2.35392]	[2.34069]	[2.35887]	[2.34679]	[2.35405]	[2.34159]
%union	0.61695***	0.60884***	0.61796***	0.61026***	0.61674***	0.60878***	0.61603***	0.60785***
	[2.81071]	[2.77079]	[2.81366]	[2.77418]	[2.80751]	[2.76648]	[2.80545]	[2.76841]
%high school education	-0.24110**	-0.23633**	-0.24238**	-0.23749**	-0.24301**	-0.23890**	-0.24212**	-0.23612**
	[2.05442]	[1.99030]	[2.06494]	[1.99975]	[2.07277]	[2.01568]	[2.06415]	[1.99421]
%some college education	0.07508	0.08696	0.07486	0.08688	0.07463	0.08591	0.07409	0.08454
	[0.61925]	[0.71931]	[0.61710]	[0.71814]	[0.61509]	[0.71011]	[0.60940]	[0.69604]
%college education and higher	0.19982	0.22573	0.19916	0.22476	0.19952	0.22429	0.19970	0.22442
	[1.33229]	[1.49202]	[1.32679]	[1.48323]	[1.32646]	[1.47750]	[1.32865]	[1.48164]
Constant	2.11525***	2.11975***	2.12225***	2.12128***	2.11817***	2.11720***	2.11746***	2.11207***
	[16.45037]	[16.39734]	[16.46337]	[16.35980]	[16.40713]	[16.35960]	[16.34897]	[16.31008]
State-specific time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation-specific time trends	No	Yes	No	Yes	No	Yes	No	Yes
Observations	25663	25663	25663	25663	25663	25663	25663	25663
R-squared	0.89549	0.89963	0.89537	0.89948	0.89529	0.89933	0.89529	0.89946
T test: Adopt+AdoptxLow=0	**0.01503**	**0.02079****	**0.01242**	**0.01649***	**0.00783**	**0.01019**	**-0.00072**	**-0.01043**
T-statistic_1	**[1.56456]**	**[2.13646]**	**[1.42003]**	**[1.83118]**	**[1.04272]**	**[1.29341]**	**[0.08844]**	**[1.41761]**
T test: Adopt+AdoptxHigh=0	**0.00166**	**-0.01244**	**-0.00719**	**-0.01394**	**-0.00255**	**-0.00893**	**-0.00250**	**-0.00475**
T-statistic_2	**[0.12971]**	**[1.11960]**	**[0.63613]**	**[1.23874]**	**[0.28172]**	**[0.97939]**	**[0.42147]**	**[0.79372]**
F test: Adopt=AdoptxLow=AdoptxHigh=0	3.21181	1.59784	0.73147	1.15767	0.36263	0.93350	0.65716	3.27997
Prob > F	0.02195	0.18758	0.53306	0.32430	0.78000	0.42343	0.57835	0.01999

Robust (absolute value of) t statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7A: Good Faith Exception (All Area) [Dep Var: LN(emp/pop)]
No Controls for Characteristics

	Any kind of training		School training		Formal training		Informal training	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Adopt(GF)	**0.03841***	**0.03762***	**0.00718**	**0.00725**	**0.03539****	**0.03402***	**-0.00319**	**-0.00294**
	[1.89536]	**[1.80978]**	**[0.43559]**	**[0.43266]**	**[2.00399]**	**[1.86413]**	**[0.16187]**	**[0.14517]**
Adopt(GF)xLow(Any training)	-0.13524***	-0.13040**						
	[2.58653]	[2.43674]						
Adopt(GF)xHigh(Any training)	0.07570**	0.07408**						
	[2.18699]	[2.15365]						
Adopt(GF)xLow(School training)			-0.11197**	-0.10796**				
			[2.21336]	[2.10651]				
Adopt(GF)xHigh(School training)			0.12705***	0.12435***				
			[4.73075]	[4.51987]				
Adopt(GF)xLow(Formal company training)					-0.12633**	-0.12076**		
					[2.54370]	[2.37422]		
Adopt(GF)xHigh(Formal company trianing)					0.05302**	0.05395**		
					[2.42408]	[2.46234]		
Adopt(GF)xLow(Informal training)							-0.02582	-0.02292
							[0.41309]	[0.36076]
Adopt(GF)xHigh(Informal training)							0.04189**	0.04066*
							[2.00002]	[1.90497]
Constant	-5.59145***	-5.59270***	-5.59538***	-5.59657***	-5.58650***	-5.58816***	-5.57632***	-5.57791***
	[74.07930]	[73.62191]	[73.97742]	[73.49288]	[74.60873]	[74.24346]	[74.44326]	[74.04579]
State-specific time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation-specific time trends	No	Yes	No	Yes	No	Yes	No	Yes
Observations	313951	313951	313951	313951	313951	313951	313951	313951
R-squared	0.82788	0.83343	0.82835	0.83388	0.82736	0.83294	0.82622	0.83187
T test: Adopt+AdoptxLow=0	**-0.09682*****	**-0.09277****	**-0.10479*****	**-0.10071*****	**-0.09093*****	**-0.08675****	**-0.02900**	**-0.02586**
T-statistic_1	**[2.72708]**	**[2.54398]**	**[2.77389]**	**[2.60770]**	**[2.61920]**	**[2.43637]**	**[0.63573]**	**[0.55663]**
T test: Adopt+AdoptxHigh=0	**0.11412*****	**0.11171*****	**0.13423*****	**0.13160*****	**0.08841*****	**0.08797*****	**0.03870**	**0.03772**
T-statistic_2	**[2.75684]**	**[2.66979]**	**[3.84827]**	**[3.67605]**	**[2.74551]**	**[2.69899]**	**[1.34881]**	**[1.28204]**
F test: Adopt=AdoptxLow=AdoptxHigh=0	2.81781	2.56351	7.67691	7.08102	2.70450	2.59203	1.34228	1.21911
Prob > F	0.03752	0.05286	0.00004	0.00009	0.04373	0.05088	0.25858	0.30092

Robust (absolute value of) t statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7B: Good Faith Exception (All Area) [Dep Var: LN(avg wage)]
No Controls for Characteristics

	Any kind of training		School training		Formal training		Informal training	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Adopt(GF)	**-0.00372**	**-0.00285**	**0.00805**	**0.00883**	**0.00529**	**0.00606**	**-0.01322**	**-0.01161**
	[0.47650]	**[0.36225]**	**[0.94106]**	**[1.02021]**	**[0.58074]**	**[0.66242]**	**[1.62800]**	**[1.35387]**
Adopt(GF)xLow(Any training)	0.00291	0.00282						
	[0.17025]	[0.16503]						
Adopt(GF)xHigh(Any training)	0.00390	0.00258						
	[0.29642]	[0.18513]						
Adopt(GF)xLow(School training)			-0.01657	-0.01686				
			[0.91579]	[0.92887]				
Adopt(GF)xHigh(School training)			-0.01574	-0.01616				
			[1.38049]	[1.39361]				
Adopt(GF)xLow(Formal company training)					-0.01206	-0.01242		
					[0.70747]	[0.72727]		
Adopt(GF)xHigh(Formal company trianing)					-0.01359**	-0.01400**		
					[2.12572]	[2.16154]		
Adopt(GF)xLow(Informal training)							0.03049***	0.02799**
							[2.74411]	[2.48475]
Adopt(GF)xHigh(Informal training)							0.00844	0.00737
							[1.05240]	[0.88694]
Constant	2.36311***	2.36184***	2.36459***	2.36317***	2.36475***	2.36332***	2.36397***	2.36252***
	[157.11911]	[155.39774]	[158.66762]	[156.80020]	[160.02056]	[158.07326]	[161.82910]	[159.85625]
State-specific time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation-specific time trends	No	Yes	No	Yes	No	Yes	No	Yes
Observations	26568	26568	26568	26568	26568	26568	26568	26568
R-squared	0.93318	0.93771	0.93325	0.93778	0.93322	0.93776	0.93335	0.93786
T test: Adopt+AdoptxLow=0	**-0.00081**	**-0.00002**	**-0.00852**	**-0.00804**	**-0.00677**	**-0.00636**	**0.01726**	**0.01638**
T-statistic_1	**[0.05250]**	**[0.00155]**	**[0.51732]**	**[0.48348]**	**[0.47889]**	**[0.44660]**	**[1.53183]**	**[1.49176]**
T test: Adopt+AdoptxHigh=0	**0.00018**	**-0.00026**	**-0.00769**	**-0.00734**	**-0.00830**	**-0.00793**	**-0.00478**	**-0.00424**
T-statistic_2	**[0.01033]**	**[0.01462]**	**[0.52262]**	**[0.49706]**	**[0.75523]**	**[0.71986]**	**[0.59882]**	**[0.52665]**
F test: Adopt=AdoptxLow=AdoptxHigh=0	0.23064	0.11998	2.63973	2.69699	2.03516	2.11953	3.21598	2.63104
Prob > F	0.87510	0.94839	0.04773	0.04419	0.10662	0.09544	0.02182	0.04830

Robust (absolute value of) t statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 8A: Good Faith Exception (All Area) [Dep Var: LN(emp/pop)]
Controls for Characteristics are at the State Level

	Any kind of training		School training		Formal training		Informal training	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Adopt(GF)	**0.02874**	**0.02796**	**-0.00251**	**-0.00242**	**0.02569**	**0.02432**	**-0.01289**	**-0.01263**
	[1.47047]	**[1.39294]**	**[0.15941]**	**[0.15150]**	**[1.51116]**	**[1.38239]**	**[0.67514]**	**[0.64318]**
Adopt(GF)xLow(Any training)	-0.13526***	-0.13042**						
	[2.58682]	[2.43702]						
Adopt(GF)xHigh(Any training)	0.07569**	0.07407**						
	[2.18675]	[2.15324]						
Adopt(GF)xLow(School training)			-0.11195**	-0.10795**				
			[2.21202]	[2.10525]				
Adopt(GF)xHigh(School training)			0.12707***	0.12436***				
			[4.73280]	[4.52156]				
Adopt(GF)xLow(Formal company training)					-0.12629**	-0.12073**		
					[2.54176]	[2.37233]		
Adopt(GF)xHigh(Formal company trianing)					0.05308**	0.05401**		
					[2.42774]	[2.46588]		
Adopt(GF)xLow(Informal training)							-0.02584	-0.02295
							[0.41351]	[0.36123]
Adopt(GF)xHigh(Informal training)							0.04192**	0.04069*
							[2.00104]	[1.90589]
%male	0.33286***	0.32767***	0.33140***	0.32627***	0.33438***	0.32924***	0.33349***	0.32826***
	[4.21310]	[4.22599]	[4.19840]	[4.21231]	[4.19329]	[4.21028]	[4.24495]	[4.26340]
%black	-0.23668***	-0.23227***	-0.23425***	-0.22989***	-0.23430***	-0.22996***	-0.23246***	-0.22814***
	[2.95529]	[2.94831]	[2.90384]	[2.89766]	[2.90741]	[2.90224]	[2.88648]	[2.88241]
%age18-35	0.75363***	0.74972***	0.75280***	0.74897***	0.75177***	0.74799***	0.75178***	0.74794***
	[12.53420]	[12.88667]	[12.53716]	[12.88975]	[12.47239]	[12.83314]	[12.53411]	[12.90019]
%age36-55	0.60183***	0.60149***	0.60306***	0.60276***	0.60421***	0.60394***	0.60741***	0.60699***
	[9.02820]	[9.36101]	[9.04565]	[9.37720]	[9.09099]	[9.42866]	[9.09885]	[9.43524]
%married	-0.00889	-0.01268	-0.00724	-0.01106	-0.00776	-0.01167	-0.00876	-0.01260
	[0.19244]	[0.28072]	[0.15669]	[0.24467]	[0.16815]	[0.25876]	[0.18969]	[0.27933]
%union	0.36059***	0.35902***	0.36119***	0.35959***	0.36046***	0.35891***	0.35984***	0.35821***
	[4.43560]	[4.45544]	[4.45685]	[4.47566]	[4.44762]	[4.46707]	[4.40044]	[4.41924]
%high school education	0.19100***	0.20146***	0.19306***	0.20344***	0.19208***	0.20256***	0.19056***	0.20134***
	[3.26316]	[3.48806]	[3.31892]	[3.54553]	[3.30844]	[3.53685]	[3.28458]	[3.51588]
%some college education	0.27617***	0.29486***	0.27630***	0.29490***	0.27700***	0.29571***	0.27823***	0.29705***
	[3.61340]	[3.96504]	[3.63498]	[3.98581]	[3.63934]	[3.99412]	[3.63371]	[3.99294]
%college education and higher	0.25801***	0.26515***	0.25916***	0.26624***	0.25736***	0.26451***	0.25959***	0.26690***
	[3.44041]	[3.58984]	[3.45135]	[3.60131]	[3.42970]	[3.58017]	[3.46369]	[3.61470]
Constant	-6.38339***	-6.38734***	-6.38889***	-6.39277***	-6.38053***	-6.38492***	-6.37030***	-6.37474***
	[69.39526]	[70.11988]	[69.09445]	[69.78753]	[69.37286]	[70.15690]	[69.64969]	[70.39282]
State-specific time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation-specific time trends	No	Yes	No	Yes	No	Yes	No	Yes
Observations	313951	313951	313951	313951	313951	313951	313951	313951
R-squared	0.82809	0.83364	0.82855	0.83409	0.82756	0.83314	0.82642	0.83207
T test: Adopt+AdoptxLow=0	**-0.10651*** **	**-0.10245*** **	**-0.11446*** **	**-0.11037*** **	**-0.10060*** **	**-0.09640*** **	**-0.03873**	**-0.03558**
T-statistic_1	**[2.99477]**	**[2.80635]**	**[3.01665]**	**[2.84744]**	**[2.88508]**	**[2.69826]**	**[0.84699]**	**[0.76446]**
T test: Adopt+AdoptxHigh=0	**0.10444** **	**0.10204** **	**0.12456*** **	**0.12194*** **	**0.07877** **	**0.07833** **	**0.02903**	**0.02805**
T-statistic_2	**[2.53461]**	**[2.45084]**	**[3.60754]**	**[3.44080]**	**[2.47911]**	**[2.43698]**	**[1.02739]**	**[0.96835]**
F test: Adopt=AdoptxLow=AdoptxHigh=0	3.63909	3.13481	8.75455	7.78160	3.52951	3.20564	2.32362	1.88801
Prob > F	0.01218	0.02437	0.00001	0.00003	0.01417	0.02212	0.07283	0.12915

Robust (absolute value of) t statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 8B: Good Faith Exception (All Area) [Dep Var: LN(avg wage)]
Controls for Characteristics are at the State Level

	Any kind of training		School training		Formal training		Informal training	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Adopt(GF)	**-0.00550**	**-0.00479**	**0.00627**	**0.00688**	**0.00350**	**0.00411**	**-0.01505****	**-0.01361***
	[0.75514]	**[0.65948]**	**[0.77150]**	**[0.84340]**	**[0.40352]**	**[0.47427]**	**[1.96725]**	**[1.69773]**
Adopt(GF)xLow(Any training)	0.00287	0.00279						
	[0.16810]	[0.16284]						
Adopt(GF)xHigh(Any training)	0.00394	0.00262						
	[0.29939]	[0.18756]						
Adopt(GF)xLow(School training)			-0.01658	-0.01687				
			[0.91558]	[0.92863]				
Adopt(GF)xHigh(School training)			-0.01573	-0.01616				
			[1.38056]	[1.39379]				
Adopt(GF)xLow(Formal company training)					-0.01207	-0.01243		
					[0.70697]	[0.72663]		
Adopt(GF)xHigh(Formal company trianing)					-0.01357**	-0.01398**		
					[2.11721]	[2.15337]		
Adopt(GF)xLow(Informal training)							0.03053***	0.02804**
							[2.74832]	[2.48861]
Adopt(GF)xHigh(Informal training)							0.00849	0.00742
							[1.05736]	[0.89207]
%male	0.15224	0.14941	0.15249	0.14974	0.15202	0.14928	0.14978	0.14724
	[0.59395]	[0.57551]	[0.59568]	[0.57749]	[0.59276]	[0.57471]	[0.58273]	[0.56568]
%black	-0.17203	-0.16968	-0.17236	-0.17003	-0.17189	-0.16955	-0.17280	-0.17042
	[1.36218]	[1.30758]	[1.36374]	[1.30935]	[1.36084]	[1.30634]	[1.37204]	[1.31644]
%age18-35	0.34601**	0.35287**	0.34631**	0.35322**	0.34608**	0.35299**	0.34691**	0.35367**
	[2.36014]	[2.39838]	[2.36155]	[2.40012]	[2.36158]	[2.40024]	[2.36708]	[2.40479]
%age36-55	0.11063	0.12195	0.11037	0.12160	0.11106	0.12232	0.11196	0.12307
	[0.74693]	[0.82121]	[0.74485]	[0.81856]	[0.74950]	[0.82340]	[0.75531]	[0.82822]
%married	0.10822	0.10825	0.10839	0.10839	0.10854	0.10854	0.10749	0.10754
	[1.24617]	[1.23575]	[1.24807]	[1.23722]	[1.25060]	[1.23971]	[1.23716]	[1.22726]
%union	0.29569	0.29207	0.29604	0.29240	0.29591	0.29226	0.29623	0.29254
	[1.50201]	[1.47395]	[1.50343]	[1.47530]	[1.50178]	[1.47363]	[1.50376]	[1.47556]
%high school education	-0.17988	-0.18259*	-0.18017	-0.18294*	-0.18004	-0.18283*	-0.18066*	-0.18327*
	[1.64050]	[1.64510]	[1.64279]	[1.64783]	[1.64233]	[1.64755]	[1.64743]	[1.65131]
%some college education	0.12105	0.12755	0.12028	0.12679	0.12038	0.12685	0.12022	0.12682
	[0.89361]	[0.94168]	[0.88686]	[0.93480]	[0.88922]	[0.93703]	[0.88593]	[0.93483]
%college education and higher	0.29866**	0.31165**	0.29809**	0.31109**	0.29868**	0.31164**	0.29982**	0.31271**
	[2.06190]	[2.12883]	[2.05587]	[2.12262]	[2.05925]	[2.12584]	[2.07260]	[2.13939]
Constant	2.04730***	2.03937***	2.04888***	2.04081***	2.04885***	2.04078***	2.04927***	2.04108***
	[14.35864]	[14.14409]	[14.39613]	[14.18038]	[14.34972]	[14.13268]	[14.34494]	[14.12672]
State-specific time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation-specific time trends	No	Yes	No	Yes	No	Yes	No	Yes
Observations	26568	26568	26568	26568	26568	26568	26568	26568
R-squared	0.93334	0.93788	0.93341	0.93795	0.93339	0.93793	0.93352	0.93802
T test: Adopt+AdoptxLow=0	**-0.00263**	**-0.00200**	**-0.01032**	**-0.00999**	**-0.00857**	**-0.00832**	**0.01548**	**0.01443**
T-statistic_1	**[0.17424]**	**[0.13086]**	**[0.64098]**	**[0.61663]**	**[0.62550]**	**[0.60462]**	**[1.44926]**	**[1.38779]**
T test: Adopt+AdoptxHigh=0	**-0.00157**	**-0.00217**	**-0.00947**	**-0.00927**	**-0.01007**	**-0.00987**	**-0.00656**	**-0.00618**
T-statistic_2	**[0.09074]**	**[0.12299]**	**[0.65516]**	**[0.64023]**	**[0.94222]**	**[0.92304]**	**[0.87474]**	**[0.82308]**
F test: Adopt=AdoptxLow=AdoptxHigh=0	0.36235	0.22384	2.73418	2.79466	2.08461	2.16519	3.44067	2.83499
Prob > F	0.78020	0.87988	0.04203	0.03873	0.09992	0.08986	0.01603	0.03667

Robust (absolute value of) t statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%