Local Labor Market Conditions and Stock Options Incidence: A Study of the Information Technology Sector

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Abstract

This article focuses on firms' use of stock options to reduce exposure to labor market pressure during industry booms. If firm stock price is positively related to industry growth and industry growth is positively related to compensation at alternative employers, then stock options can be used to index total employee compensation without increasing wages. The empirical analysis, based on a proprietary survey of information technology (IT) professionals, demonstrates that stock option incidence in the IT sector is positively correlated with regional labor market sensitivity to industry shocks. I conclude that stock options are implemented in a manner consistent with the reduction of labor market pressure.

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1 Introduction

Stock option grants to rank-and-file employees are a powerful human resources tool that can be implemented to achieve a variety of goals. Options can be used to align principal and agent incentives, motivate workers towards specific goals, provide wage-bill flexibility to financially constrained firms, reduce employers' tax liability, hide employee compensation from outside shareholders, and reduce upward wage pressure during industry booms. This paper focuses on the wage pressure reduction aspects of stock option grants. Specifically, during an industry boom, stock options can reduce regional wage pressure by increasing employees' total compensation without necessitating wage re-negotiation.

Stock options give workers the option to buy shares of their employer's stock at some point in the future at the share price at the time of award. Typically, upon receipt of the option, employees must remain employed at the firm until the option vests[1], at which point, they may purchase the firm's stock at the *strike price*, typically the stock price at time of award. If the stock price is greater than the strike price, then it is *"in the money"*. If the option is "in the money" at the end of the vesting period, the option holder receives immediate profit upon exercising her option. If the stock price does not increase over the strike price, then the employee does not exercise the option and receives no benefit.

If the stock price of the average firm is positively related to overall industry growth, options operate as pro-cyclical bonuses. If an industry grows over the vesting period, the expected value of options are positive. If the industry does not grow, the expected value of options are zero. Because of their pro-cyclical return, options may be used to retain workers during industry booms.

In boom markets, there is industry-wide growth that is typically accompanied by increased demand for labor and higher wages. This increases the likelihood of a worker receiving an alternate job offer that results in her leaving her current employer. However, in boom markets workers receive a potential windfall at the end of their vesting period, so there is a (potentially) strong motivation to stay with the current employer and realize that gain. So, when industry growth is strong, a firm's workers' outside options improve, while at the same time the value of their options increase strengthening the incentive for employees to stay with their current employer. If a firm expects to receive a positive industry-wide shock (and wage renegotiation is costly), then the firm can use stock option grants to index their employees' wages to their alternative wages and prevent worker desertion. I refer to this effect as the "insulation/retention effect". This point is explored by Oyer (2001).

Outstanding stock options that are "in the money" are useful to the employer because they allow the employer to avoid repeated contract renegotiation during booms. Also, "in the money" option incidence allows total compensation to be flexible downward during a recession. Because wages are typically downwardly rigid, it is costly for an employer to reduce wages in a recession. For the average firm, "in the money" stock options lose value during industry recessions, effectively reducing the total expected compensation to employees without requiring costly wage re-negotiation.

I hypothesize that firms use stock options in a manner that is consistent with reducing upward wage pressure. I expect options to be more prevalent in regions where wages are

[1] Typical vesting period is four years with 25% vesting at the end of each year.

highly sensitive to industry shocks (the retention/insulation effect). To test my hypothesis, I develop a simple model of the relationship between local labor market sensitivity to industry shocks and firms' likelihood to offer stock options. I then test the implications of the model using data from an exclusive survey of information technology professionals augmented with data from the Current Population Survey - Merged Outgoing Rotation Groups. I examine outcomes in the information technology (IT) sector because the labor market for IT workers is likely to satisfy the conditions necessary for stock options to be both prevalent and an effective wage pressure reduction device. As I develop below, pro-cyclical contingency-based compensation (stock options) can be used to reduce wage pressures if **all** of the following conditions apply[2]:

1. The firm is in an industry that experiences large shocks.
2. Turnover is costly to the firm.
3. Alternative wages move with own-firm stock price.

Many IT professionals are employed in high-tech industries - industries which are known for their volatility. Turnover can be very costly for the employers of IT professionals. For example, if a software application developer leaves in the middle of a complex, undocumented, and unfinished project, it may be very difficult for a new employee to resume the project. In response to the third condition, I demonstrate below that in many regions, alternative wage and employment is positively correlated with an industry index. Because the IT workforce satisfies all three conditions above, it is an excellent environment to study option incidence, in fact 40% of IT workers in my sample receive options.

An implication of the third condition listed above is that workers in regions where employment demand and alternative wages are highly sensitive to industry shocks are more likely to receive stock options than workers in regions where employment demand and wages are not sensitive to industry shocks. Using the information technology data and CPS data, I find that even after controlling for worker characteristics and firm characteristics, workers in states where both employment and wages are highly correlated with industry shocks are more likely to receive options than workers in states where wages and employment are uncorrelated with industry shocks.

This paper proceeds as follows. In Section 2, I discuss several reasons why firms may offer stock options and the previous literature testing those reasons. In Section 3, I describe a model that relates local labor market sensitivity to industry shocks to a firm's decision to offer stock options. In Section 4, I present a new and proprietary set of data collected from a survey of information technology professionals and I discuss my extracts from the Current Population Survey - Merged Outgoing Rotation Groups. I use the data from the IT sector to analyze the empirical implications of the model in Section 5 and perform robustness checks in Section 6. In Section 7, I summarize and discuss the results.

[2]The first condition has been explored by Oyer (2001). This article focuses primarily on the third condition.

2 Why Firms May Offer Stock Options

There are many candidate reasons for why firms offer stock options to their employees. The strongest reasons include: stock options allow employers to align principal-agent incentives, stock options provide wage-bill flexibility when firms have capital constraints, stock options can be used to sort and screen workers, and stock options can be implemented as a form of conditional contract to reduce turnover.

Stock options are an increasingly common form of compensation. Mehran and Tracy (2001) examine the amount of change in aggregate compensation per hour that is attributable to stock options using data from firms' annual reports and proxy statements from 1992-1999. They find that growth in options explains a large portion of growth in overall compensation in the 1990s and that sensitivity of executive pay to performance increased at the same time.

Using data from 1980 to 1994, Hall and Liebman (1998) concur with Mehran and Tracy's position that option compensation is growing, but Hall and Liebman demonstrate that the trend towards options comprising a larger portion of executive compensation and the trend toward increased sensitivity of executive compensation to firm performance has existed since the 1980s.

2.1 Stock Options as Incentives

Whether stock options provide a motivational effect large enough to align principal and agent incentives is an open question in the literature. Stock option incentive effects are an off-shoot of the extensive profit sharing literature[3], but looking specifically at the incentive effects of stock options is a young field.

Among the first researchers of the motivational effects of stock options, Jensen and Murphy (1990) analyze the compensation packages of 2,213 CEOs from 1974 to 1986. They find that the incentive provided by stock options is small, even to top management. According to their estimates for CEOs in this time period, a $1,000 increase in firm value is worth approximately 45 cents of additional compensation over the lifetime of the CEO.

Meulbroek (2000) also questions the incentive power of stock options. She demonstrates that if executives hold enough stock options to be aligned with the principals, then the executives will have a portfolio of investments that is under-diversified. Because the executives are under-diversified, they under-value their stock which undermines the incentive alignment effects of stock ownership. Also, stock options have no down-side risk which counter-acts any risk sharing and diminishes incentive effects (Young and Quintero 1995).

In a study of 229 firms that offer broad-based options, Sesil, et al. (2002) do not find evidence that broad-based stock options are correlated with firm growth. Similarly, Yermack (1995) demonstrates that stock options to managers do not reduce agency costs.

On the other hand, Ittner, Lambert, and Larcker (2001) demonstrate that in young firms, stock option grants have a positive effect on firm stock performance. Their findings are consistent with the hypothesis that options have a significant effect on motivation. Although Nohel and Todd 2002 argue that managers potentially only need a small number of stock options to align incentives, any incentive effect for executives would be far greater than the

[3] For a review of the microeconomic impacts of profit sharing see Kruse (1992).

incentive effects for non-executives. Non-executives tend to have compensation packages that are less sensitive to firm performance and also tend to have less direct effect on firm performance.

Using data from 1996 to 1999, Liang and Weisbenner (2001) demonstrate that options grants are highly correlated with both past firm performance and past industry performance. Specifically, if the firm did well in the previous period, stock option incidence is likely to be greater than if the firm did poorly. Their findings suggest that firms may use stock options not as an *ex ante* incentive device, but as an *ex poste* reward.

Another common explanation for stock option grants to non-executives is that stock options allow employers to defer compensation and maintain investment flexibility when credit is expensive. Core and Guay (2001) examine the stock option grants and exercise decision of non-executives in 756 firms from 1994-1997. They find that credit constrained firms have larger stock option programs. They also present evidence to support the theory that stock options are used to attract and retain workers as well as align incentives.

In contrast to Core and Guay, Bens, Nagar, and Wong (2000) examine some of the hidden costs of employee stock options and find that firms with large stock option programs divert resources away from capital investment into the stock re-purchases necessary to cover their position. This suggests that firms tend to negate any ability to increase current capital investment and defer labor costs.

2.2 Stock Options as Conditional Contracts

Stock options provide a form of conditional contract where compensation is explicitly tied to firm performance. Firms can use conditional contracts to insulate employment from the risks of uncertain product and labor market conditions. Contracts conditional on economic conditions allow firms to adjust wages in the face of unforeseen labor supply and demand shocks (Hall and Lilien 1982). Blanchard (1979) argues that explicit wage indexing has significant beneficial effects on the economy.

Conditional contracts are particularly effective because firms and workers tend to overreact to product demand shocks. Firms layoff too many workers in bust markets, and employees quit too rapidly in boom markets (Hall and Lazear 1984). Similarly, Card (1990) demonstrates that unexpected wage changes are inversely related to employment responses. Contingent contracts can mitigate the exposure of both firms and employees to product demand volatility and reduce inefficient separations.

Blakemore, et al (1987) demonstrate how a two part compensation system with a fixed wage and a flexible bonus can reduce the level of inefficient separations. Using the Panel Survey of Income Dynamics, they show that bonus incidence is negatively related to turnover.

Assuming that holding a stock option represents an investment by the worker in the company and her future with that company, holding stock options has the same retention effects as firm specific human capital. Firm-specific human capital is only valuable to the employee when the employer-employee relationship continues (Hashimoto 1979). Hashimoto (1981) develops an extension to the traditional Becker model of wage dynamics where investment in human capital is shared between employer and employee. Sharing the costs of training decreases the likelihood of inefficient separations. Stock option costs are shared between the employer and employee, so stock options have the same effect on separations. These relationships hold even when workers are heterogeneous (Becker and Lindsay 1994).

Oyer and Schaefer (2002) argue that in all but the smallest firms, stock options have no incentives for the rank-and-file employees. They assert that stock options have larger effects to screen workers based on their expectations on firm performance as well as to retain workers. Hermalin (2002) shows how short-term contracts can be used to screen workers based on their abilities. Stock options can be viewed as a short-term contract because they provide only near-term rewards to employees.

When workers' alternative wages are correlated to the value of their stock options, options can be used to index wages without costly renegotiation (Oyer 2001). In an industry boom, workers' alternative wages will increase, increasing their incentive to leave the current employer. However, if employees holds stock options, option value increases during an industry boom which, in turn, increases the incentive for workers to stay with their current employer. I explore this framework in more detail in the rest of the paper.

My contribution to the literature is a microeconomic analysis of stock option implementation for non-executives. This will also add to the understanding of high-tech labor markets and the effect of local labor market conditions on equity compensation, incentives, and risk-sharing.

In the next section, I develop a model examining the optimal allocation of stock options given regional heterogeneity in local labor market sensitivities to industry shocks.

3 Model: Retaining Workers in a Volatile Environment

In this model, I analyze the relationship of local labor market conditions and firms' stock options policies. If employees have low mobility costs within a region, but high mobility costs between regions, than each local labor market is effectively isolated. Within each region, the responses of employment and wages to an industry-wide shock capture the sensitivity of the local labor market to industry volatility. To develop competitive compensation packages, employers need to understand how the local labor market responds to industry shocks. If the employment response to an industry shock is large, then during a boom, many employers will be competing for workers and firm profits will be high, thus the environment is conducive to firms implementing stock options to reduce labor market pressure.

I present a model where industry shocks are positively correlated with both firm profits and employees' outside alternatives. Further, the effect of an industry shock varies according to regional labor market sensitivity, so I am able to model the role of regional heterogeneity in employment and compensation outcomes. The key result of the model is that firms in areas where labor market outcomes are very sensitive to industry shocks are more likely to offer options than firms in regions where labor market outcomes are insensitive to industry shocks. In the next subsection, I provide an overview of the model.

3.1 Overview

The formal model describes a two-period economy where an employee is offered a compensation package in period 1 consisting of a wage and a bonus, where the bonus is a share of the firm's profits in period 2. In period 2, an industry-wide shock is revealed and the employee receives an alternative wage offer from a competing firm in the region. If the alternative wage is greater than the value of the employee's compensation package, the original firm must choose to renegotiate the wage or lose the employee, both of which are costly. Wages may be costly to adjust for several reasons including the physical cost of re-negotiating all employee contracts and the penalty that shareholders may place on the company in the face of a rising wage bill. If shareholders will penalize the company for rising compensation costs, then there is incentive for firms to hide compensation in the form of un-expensed stock option grants.

The firm's period 1 problem is to design an optimal compensation package given a signal on the upcoming industry shock. First, I outline the conditions necessary for an employee to receive an alternative offer and then I develop the conditions necessary for the hiring firm to desire to retain an employee given that the employee receives an alternative employment offer.

In an industry boom (i.e. after a positive industry shock has occurred), a worker may receive an alternative employment offer if both of the following conditions are satisfied:

- (1) the industry boom increases employment demand in the region.
- (2) the employee's expected marginal revenue product at an alternative employer within the region is greater than or equal to her current compensation.

Current employers will want to keep an existing employee who receives an alternative offer or attract a new employee if:

- (3) the sum of an employee's marginal revenue product at the current firm and the turnover cost is greater than or equal to the alternative wage offer.

If all of the the above conditions are satisfied, then profit-maximizing employers may assign a bonus in period 1 consisting of a share of period 2 firm profits in order to retain specific employees and attract new employees.

If any of the three conditions are not satisfied, then it is not profit maximizing for a firm to offer this contingency-based bonus. For example, consider the following cases where one of the conditions fail:

Condition 1 is not satisfied (The South Dakota Case).

Consider a region where employment of information technology professionals is not highly correlated with industry growth. This might occur in a region with few technology firms or firms that experience little market volatility. In this case, an industry shock will have little effect on employment within the region. Firms will not be competing to retain employees, and consequently will be unlikely to need to offer stock options as a retention device.

Condition 2 is not satisfied (The Mainframe Analyst Case).

Consider an employee who has extensive firm-specific skills and low transferable skills. It is likely that this worker will receive a wage from their current employer that is greater than their marginal revenue product at an alternative employer. The alternative employer will not offer a position with higher compensation to this employee, so the current employer will not need to offer stock options to prevent desertion.

Condition 3 is not satisfied (The Web Designer Case).

Consider an employee with no firm-specific skills. If turnover costs are sufficiently low, it is not necessary to retain this worker. The current employer will not offer stock options to this worker because the position could easily be filled by someone else.

To summarize, a firm will offer a share of the firm's profits to retain a current employee during an industry boom if the marginal revenue product of the employee is greater than the available alternative wage conditional upon the response of the local labor market to the boom. In the next section, I formalize the above discussion.

3.2 Stock Option Policy

I describe a two-period economy where in the first period, firms offer a wage and a bonus consisting of a share of firm profits in the next period. An industry demand shock occurs in the second period and employees may receive an alternative wage offer. If the alternative offer has greater value than the current compensation package, the employing firm must choose to counter-offer or lose the employee, both of which are costly.

Assumptions:

1. Firms maximize profits, are risk neutral and identical except for location.
2. Workers have linear utility and differ by a vector of observable human capital characteristics, X, that define their occupation and skills.
3. The cost for employees to leave their current employer is T, where T varies across employers and is known to the employer.
4. Aggregate labor demand for workers with occupation X in region j is a function of the size of the industry, $L_{d,j} = L_d(\text{size}, X)$. Normalize so that in period 1, industry size $= 0$, thus initially, $L_{d,j} = L_{d,j}(0, X)$. Assume the derivative of labor demand with respect to industry size is positive.
5. Wages are downwardly rigid, and are costly to adjust.
6. Employees do not directly affect firm profits, Π.
7. A positive industry shock θ affects the profits and labor demand of every firm. The size of the shock is known with certainty.

8. Local labor markets j differ by the sensitivity of employment demand to industry shocks, $\eta_{d,j}$ (i.e. after a shock of size θ, labor demand for workers of type X shifts to $L'_{d,j} = L_{d,j}(\eta_{d,j}\ \theta, X))$, and the sensitivity of employment supply to industry shocks, $\eta_{s,j}$ (i.e. after a shock of size θ, labor supply of workers of type X shifts to $L'_{s,j} = L_{s,j}(\eta_{s,j}\ \theta, X))$.

9. Firms have cost τ of replacing an employee and cost γ associated with offering options. The cost of replacing a worker includes the cost of hiring a new employee and any inefficiency associated with turnover. The cost of offering options includes administrative costs as well as institutional costs such as shareholder penalties to stock dilution.

Time-line:

1. Firms receive a signal θ on the state of the industry in period 2. Expected firm profits in periods 1 and 2 are $\Pi_1 = \Pi(0)$ and $\Pi_2 = \Pi(\theta)$.

2. A firm hires an employee with characteristics X and offers the compensation package (w, b) where $w = w(L_{s,j}(0, X), L_{d,j}(0, X))$ is the wage and b is a share of the growth in firm profits between period 1 and period 2. The return to holding b stock options is:

$$\begin{aligned} &b(\Pi(\theta) - \Pi(0)) \ \text{ if } \ \theta > 0 \\ &\qquad\qquad\qquad 0 \ \text{ otherwise} \end{aligned}$$

3. At the end of period 1, the shock θ occurs.

4. The employee receives an alternative wage offer of $w' = w(L'_{s,j}, L'_{d,j})$, where $L'_{s,j} = L_{s,j}(\eta_{s,j}\,\theta, X)$ is the aggregate labor supply in the second period and $L'_{d,j} = L_{d,j}(\eta_{d,j}\,\theta, X)$ is the aggregate labor demand in the second period. If the alternative wage offer is greater than the current compensation package plus worker switching costs, i.e.

$$w' > w + b(\Pi(\theta) - \Pi(0)) + T \tag{1}$$

then the current employer chooses to renegotiate or lose the employee, both of which are costly.

5. The economy ends.

The problem for the firm is to set b to maximize profits. If the firm is profit maximizing, optimal b^* will be set such that Condition 1 binds at the minimum cost to the firm. Condition 1 binds when:

$$b^* = \frac{\Delta w_j(\theta, X) - T}{\Pi(\theta) - \Pi(0)} \tag{2}$$

Where $\Delta w_j(\theta, X) = w(L'_{s,j}, L'_{d,j}) - w(L_{s,j}, L_{d,j})$.

That is, the share of the firm's increase in profits offered to a worker is equal to the workers' gain from switching divided by the total increase in profits. However, if the worker's gain from switching is less than the worker's cost of switching, the worker will not defect, and the firm will not offer any options. The worker will defect if:

$$\Delta w_j(\theta, X) - T > 0 \tag{3}$$

Assuming that the worker will defect if the worker holds no options (i.e. Condition 3 holds), the cost to the firm of not offering options, $c(0)$, is:

$$c(0) = \tau + \Delta w_j(\theta, X) \tag{4}$$

where τ is the cost of replacing the worker and $\Delta w_j(\theta, X)$ represents the increase in market wages paid to the new worker. The cost of offering a positive level of options is

$$c(b|b > 0) = b(\Pi(s) - \Pi(0)) + \gamma \tag{5}$$

At the optimal b^*, Equation 2 holds, and after substituting into Equation 5, the cost to the firm of offering $b^* > 0$ is:

$$c(b^*|b^* > 0) = \Delta w_j(\theta, X) - T + \gamma \tag{6}$$

A profit-maximizing firm will offer options when the cost of offering options is less than the cost of not offering options:

$$\Delta w_j(\theta, X) - T + \gamma < \tau + \Delta w_j(\theta, X) \tag{7}$$

Firms will offer options if and only if workers will leave if they do not have options and the cost of offering options is less than the cost of losing the worker. The optimal option grant, b^* is positive when Conditions 3 and 7 both hold. Specifically,

$$\begin{aligned} b^* &= \frac{\Delta w_j(\theta, X) - T}{\Pi(\theta) - \Pi(0)} \quad \text{if} \quad \gamma - T < \tau \quad \text{and} \quad \Delta w_j(\theta, X) - T > 0 \\ b^* &= 0 \quad \text{otherwise} \end{aligned}$$

Assuming worker switching cost, T, is randomly distributed across employees, it follows that the probability that a firm in region j, with characteristics X, and expected shock θ will offer $b > 0$ to an individual is:

$$\text{prob}(b^* > 0) = \text{prob}(\gamma - \tau < T < \Delta w_j(\theta, X)) \tag{8}$$

Equation 8 demonstrates that the probability that a firm will offer a bonus $b > 0$ decreases with the cost of administering options, increases with the replacement cost of the employee, and increases with alternative wage which is a function of local labor market sensitivity to industry shocks, $\eta_{d,j}$ and $\eta_{s,j}$ and the size of the expected industry shock θ.

3.3 Functional Specification of Stock Option Incidence

For estimation of the model, I impose the following simple functional specifications:

1. Labor Supply in region j for a worker with characteristics X is linear with slope $Y = e^{\beta X}$:

$$L_{s,j}(X) = k_j + Y w_j \tag{9}$$

2. Labor Demand is linear and is the same for all workers within the region:

$$L_{d,j}(0, X) = c_j - \alpha w_j \tag{10}$$

3. An industry shock of size θ is felt in region j as a horizontal shift in labor demand of size $\eta_{d,j}\ \theta$, and a horizontal shift in labor supply of size $\eta_{s,j}\ \theta$. Thus,

$$L_{d,j}(\eta_{d,j}\ \theta, X) = c_j - \alpha w_j + \eta_{d,j}\ \theta \tag{11}$$

and

$$L_{s,j}(\eta_{s,j}\ \theta, X) = k_j - Y w_j + \eta_{s,j}\ \theta \tag{12}$$

4. A firm will offer stock options to an employee if Conditions 3 and 7 both hold.

Equations 9 and 10 yield the market clearing wage for a worker with skills X in region j in period 1. Solving for w_j:

$$w_j = \frac{c_j - k_j}{Y + \alpha} \tag{13}$$

Similarly, Equations 11 and 12 yield the market clearing wage for a worker with skills X in region j in period 2 after a shock of size θ .

$$w' = \frac{c_j - k_j + \theta(\eta_{d,j} - \eta_{s,j})}{Y + \alpha} \tag{14}$$

Subtracting Equation 13 from Equation 14:

$$\Delta w = \frac{\theta(\eta_{d,j} - \eta_{s,j})}{Y + \alpha} \tag{15}$$

In the empirical analysis, I am concerned with the probability of an individual receiving stock options. As demonstrated in Equation 8, the probability that a worker with characteristics X in region j will receive a bonus $b > 0$ is equal to the probability that $\gamma - \tau < T < \Delta w_j(\theta, X)$. Substituting Equation 15 into Equation 8:

$$\begin{aligned} \text{prob}(b^* > 0) &= \text{prob}(\gamma - \tau < T < \frac{\theta(\eta_{d,j} - \eta_{s,j})}{Y + \alpha}) && (16) \\ &= \text{prob}(T < \frac{\theta(\eta_{d,j} - \eta_{s,j})}{Y + \alpha}) - \text{prob}(T < \gamma - \tau) && (17) \end{aligned}$$

Equation 16 leads to a very simple estimation equation. To operationalize the model, I consider the model in the typical probit framework, where T is randomly assigned across firms and has cumulative distribution function F.

Under the assumption that during booms the cost to a firm of replacing a worker, τ, is greater than the cost of administering options γ, and the cost of leaving a firm T is positive, then $\text{prob}(T < \gamma - \tau) = 0$. With this simplification, I can rewrite the previous equation as:

$$\text{prob}(b^* > 0) = 1 - F(\frac{\theta(\eta_{d,j} - \eta_{s,j})}{Y + \alpha}) \tag{18}$$

Assuming that T is distributed log-normally, and the size of the shock, θ, can be normalized to 1 over the time frame of my data, Equation 18 simplifies to

$$\text{prob}(b^* > 0) = 1 - \Phi(\log(\eta_{d,j} - \eta_{s,j}) - \beta X - c) \tag{19}$$

In the empirical section, I estimate Equation 19 using proxies, η_j's, of the sensitivity of a region's employment to economy-wide industry shocks, where η_j captures the between-state variance in $\log(\eta_{d,j} - \eta_{s,j})$. I test the hypothesis that the coefficient on the labor market sensitivity term, η_j, is positive. I calculate several specifications of η_j's for computer programmers using the 1992-2001 CPS-MORGs. Option incidence and individual characteristics come from the Dice.com survey of information technology professionals. In the next section, I discuss the data in more detail.

4 Data

In my analysis I use 3 datasets. The primary dataset is a survey of information technology professionals collected in 2000-2001. The second is an extract from the Current Population Survey Outgoing Rotation Groups including all software programmers from 1992-2001. The third dataset contains snapshots of the National Association of Securities Dealers Automated Quotations (NASDAQ) index from 1992-2001. I discuss each below.

4.1 Information Technology Professionals Salary Survey

I have acquired exclusive access to a survey of labor market outcomes of information technology professionals administered by Dice, Inc. Dice, Inc. is a service of Earthweb, Inc - "the leading provider of career development resources and technical expertise to the world's Information Technology (IT) professionals."[4] Dice Inc., provides career services assisting in the hiring, retention, and training of IT professionals and runs the leading IT professional job board ("as ranked by Media Metrix and IDC, and MeasureUp, a leading provider of preparation products for IT professional certification"[5]).

Traffic at Dice.com consists of IT professionals utilizing the site's career assistance tools. One of the tools is a salary benchmarking tool. Respondents answer a variety of questions about their demographics and current labor market outcomes and receive salary benchmarking based upon their responses. The benchmarking is only valuable if the respondent responds accurately and honestly. Dice.com has granted me access to the raw data collected through the survey tool.

There are 28,401 observations and the key variables for this paper include salary, options status, occupation, industry, age, years of technical experience, sex, firm size, location size, employment type, state and telephone area code. Because of the voluntary, on-line nature of the survey there is a certain amount of noise in the sample. In order to minimize the impact of the noise, observations are trimmed on the basis of age, salary, occupation and geographical consistency between area code and state (see Appendix Section A-1 for details

[4] http://about.dice.com
[5] http://about.dice.com

of the trimming methodology). After trimming, 18,182 observations remain in the sample. Because Dice.com offers career management tools, the dice sample may be biased towards IT professionals who are more mobile.

Data are available from June 7, 2000 to January 24, 2001. An obvious concern of the data is that they do not comprise a random sample of the population. Tables 1-3 display comparisons between the Dice data and data from the March 2000 supplement to the Current Population Survey (CPS). The CPS data consist of all observations with occupation of "computer programmer" and are trimmed according to the same rules as the Dice data.

Dice respondents earn slightly more at all but the top of the wage distribution (see Table 1). Mean wages are \$61,900 for the Dice sample compared to \$59,300 for the CPS sample. Median wages are \$60,000 and \$58,000 respectively.

Females are under-represented in the dice sample (see Table 2). Women compose only 16% of the dice sample, compared to 27% of the CPS sample.

The dice sample is substantially younger: 79% of the sample is less than 40 compared to only 66% of the CPS sample (see Table 3). However, if the dice sample represents workers who are more mobile than average, then the dice sample should be younger than the CPS tabulations.

Table 4 presents benchmarking according to regional distribution. I aggregate the data into regions based on location and sample size, and benchmark against Computer Programmers and Engineers from the Current Population Survey-Merged Outgoing Rotation Groups for 1992-2001. The Dice data substantially over-represent Northern and Southern California (by about 6 percentage points each), New York City, and Southern New Jersey and Eastern Pennsylvania, and under-represent most other regions. Southern States and the Upper Midwest are most under-represented.

Further benchmarking is performed using Bureau of Labor Statistics (BLS) data. BLS data are used to calculate the observed establishment size distribution for workers in the "Business Services" industry (the closest fit to IT). Dice establishment sizes matches up very well with the BLS calculations (see Table 5). In the dice sample, 75% of all observations are employed at locations with fewer than 500 employees, compared to 76% of the estimated BLS population.

Table 6 displays means of key variables for the entire sample as well as region-level means. California dominates the sample, accounting for a quarter of all observations. The largest five regions (Northern California, Southern California, New York City, Southern New Jersey and Eastern Pennsylvania, and Washington and Oregon) account for about 40% of the sample. Northern California has the largest average salary at \$72,110. The region including North and South Dakota, Montana, Idaho, and Wyoming (The North Central States) is the smallest, comprising about one-third of one percent of the Dice Sample and is ranked last with average annual salary of \$42,140. The national annual average salary of this sample is \$62,000.

In the total sample, 40% of all observations receive stock options. Approximately 58% of respondents in Northern California receive stock options, while only 21% of respondents in Michigan (excluding Detroit) and the North Central states receive options. Other regions with high options incidence rates include Colorado, Washington and Oregon, Northern Texas, and Boston. Regions with low stock options incidence rates include Alaska and Hawaii, Illinois (excluding Chicago), West Virginia, Kentucky and Tennessee, and Kansas and Oklahoma.

In Table 7, I present results from a Mincerian wage equation. My specification includes controls for gender, age, age^2, technical experience, technical experience^2, location size, firm size, occupational effects, industry effects, and state effects.

Despite controlling for the expected mitigating factors of experience, occupation, and industry, women earn approximately 6.7% less than their male counterparts. Technical experience has a larger impact on earnings than age. An additional year of experience results in a 6.5% increase in earnings, while an additional year of age results in a 2.2% increase in earnings. At 10 additional years, the effects are a 44% increase in earnings due to experience and a 20% increase due to age.

The omitted industry is "Computer Software" which is the most prevalent industry, and also among the top in terms of compensation. Industries associated with older technologies typically pay less than "Computer Software". Non-Profits pay 21% less that the software industry. Government employees earn about 16% less than their private sector counterparts in the software industry. Distribution and Wholesale employees earn about 12% less than the software industry. Surprisingly, the Computer Hardware industry earns approximately 11% less than the software industry. High paying industries include Banking, Internet Services, Telecommunications, and E-commerce.

High paying occupations include Strategist, Network Designer, and Project Manager. These occupations earn 30%, 21%, and 19%, more than the omitted group- "Computer Analysts". PC Technicians, Desktop Support, and Graphic Designers earn the least. Employees in these occupations earn 30%, 22%, and 17% less than computer analysts.

The Dice data are consistent with the conventional wisdom of the IT sector. California dominates the sample. Employees working in Computer Software and Internet Services lead the sector in salary compensation, they are also the youngest, have the least experience, and work at the smallest locations and firms. High-Tech related occupations, such as Applications Developer and Network Designer, exhibit positive outcomes, while Low-Tech Sector occupations, such as Mainframe Analysts, occupy the other end of the outcome spectrum.

Because of geographic, age, and gender bias in the Dice sample, I reweight all region-age-gender cells to match the weighted CPS-MORG sample detailed below.

4.2 Current Population Survey - Merged Outgoing Rotation Groups

To supplement the IT salary survey cross-sectional data with a historical component of regional labor markets, I draw upon the Feenberg/Roth-NBER Current Population Survey Merged-Outgoing Rotation Groups extracts (CPS-MORGs)[6]. I pull all computer programmers and engineers from every month between January 1992 and December 2001.

I trim the CPS-MORG data in the same manner that I trim the IT data[7]. Specifically, I exclude all observations with reported salary less than $20,000 or greater than $200,000, all observations not employed full-time, and all observations with age less than 18 or greater than 65. The remaining sample includes 53,310 observation that I aggregate into 360 region-year cells. Cell sizes vary from a low of 55 for Illinois (excluding Chicago) in 1997 to a high

[6]Available at http://www.nber.org/data/morg.html

[7]See Appendix A-1 for details

of 432 for Southern California in 1992. The mean cell size is 179.7 and the median cell size is 180.

Within each cell, I calculate the average employment and average weekly wage. I weight the observations using Final CPS weights, and I deflate wages by the Consumer Price Index to create real wages in 2001 dollars. The sample represents 825,000 programmers in 1992 to 1,200,000 programmers in 2001.

4.3 NASDAQ Index

I use the NASDAQ Composite index as a proxy for size of shocks affecting the employers of IT professionals. Although there are many stock market indices available, I use NASDAQ because it is well known and well tracked, and it covers the broad spectrum of industries that employ IT professionals. I collect the NASDAQ level on the first of the month for every month in the sample (January 1992 - December 2001)[8]. Other technology stock market indices (e.g. the NASDAQ Computer Index or the Fortune e50 index) are highly correlated with the NASDAQ composite over this time period and the results in the paper are robust to index choice.

I manipulate the NASDAQ monthly data similarly to the CPS-MORG monthly data. I aggregate the months into cells by year and then construct the average index level for each year. The cell averages increase from 595 in 1992 to 3868 in 2000 and then down to 2048 in 2001.

Labor market outcomes and NASDAQ are closely related. The yearly NASDAQ cells and national IT employment have a correlation coefficient of 0.902. National IT employment and the previous year's NASDAQ have a correlation of 0.875. Employment and NASDAQ lagged two years have a correlation of 0.881. Average IT wages across the nation and NASDAQ have a correlation of 0.856. Correlation of IT wages and NASDAQ lagged one year and NASDAQ lagged two years is 0.939 and 0.947 respectively.

5 Empirical Analysis

My methodology can be broken down into two steps. First, I use the NASDAQ and CPS-MORG data to create state-specific measures of the correlation between industry shocks and IT employment and between industry shocks and IT wages. Second, I use the estimated correlations as an explanatory variable in an option incidence model. In Section 6, I check the robustness of the results by using alternative measures of the relationship between IT labor market variables and industry shocks.

5.1 Estimating Local Labor Market-Industry Shock Sensitivities

For the first step in the analysis, I estimate the correlation between NASDAQ and mean employment and mean wages for IT professionals in 36 regions of the United States. The region-specific IT employment-NASDAQ correlation captures how closely IT employment in

[8]Data are available from http://finance.yahoo.com

the region is related to industry shocks. The IT wage-NASDAQ correlation measures how a region's wages move with NASDAQ.

Using the annual NASDAQ cells and the annual cells for each region j, I calculate:

$$\eta_j = \text{corr}(L_{j,t}, S_{t-\tau}) \tag{20}$$

Where $L_{j,t}$ is the average employment in region j in year t and $S_{t-\tau}$ is the average industry index in year $t-\tau$. I repeat the same calculations for average IT wages. The results are robust to choice of $\tau \in \{0, 1, 2\}$. In this section, I present the results for $\tau = 1$ and briefly discuss findings for $\tau = 0$ and $\tau = 2$ is Section 6.

In Table 8, I present estimated IT labor market-NASDAQ correlations. IT Wage-NASDAQ correlations are highest in Iowa, Missouri, and Nebraska; Colorado; Wisconsin and Minnesota; Washington and Oregon; and Maine, New Hampshire, and Vermont. These five regions have IT Wage-NASDAQ correlations of 0.89 or higher. The regions where wages are least correlated with NASDAQ are Alaska and Hawaii; North Dakota, South Dakota, Montana, Idaho, and Wyoming; Illinois (excluding Chicago); New Mexico and Arizona; and Massachusetts (excluding Boston). The weighted average for the IT Wage-NASDAQ correlations is 0.684 and the weighted standard deviation is 0.215.

The regions where IT employment is most closely correlated with NASDAQ are Virginia and Washington D.C.; Washington and Oregon; Utah and Nevada; Northern California; and Wisconsin and Minnesota. They all have IT Employment-NASDAQ correlations of 0.9 or higher. Regions where employment is the least correlated with NASDAQ include Illinois (excluding Chicago); Massachusetts (excluding Boston); Western Pennsylvania; Southern California; and Rhode Island and Connecticut. All have IT employment that is negatively related to NASDAQ. The regional employment weighted average of IT Employment-NASDAQ correlation is 0.669, the weighted standard deviation is 0.326.

In the next section, I use the region-specific estimates of labor market correlations as explanatory variables in the model of options incidence presented in Equation 19. The estimated IT correlations proxy for the response of employment and wages to industry shocks (the $\eta_{d,j} - \eta_{s,j}$ term described in the model).

5.2 Estimating the Relationship Between Stock Option Incidence Rates and Local IT Labor Market-Industry Shock Correlations

5.2.1 Region-Level Analysis

Using the correlations calculated above, I estimate the relationship between stock option incidence and IT labor market - NASDAQ correlation. I aggregate the individual responses from the Dice.com data to create region-level variables. With the region-level variables, I estimate the following model where option incidence rate within regions is the dependent variable:

$$O_j = \alpha\eta_j + \beta X_j + c + \epsilon_j$$

Where O_j is the percent of workers in region j who receive options, η_j is the sensitivity measure from region j, X_j is a vector of characteristics of IT employment in the region, c

is a constant, and ϵ_j is an error term. X_j includes the percent of IT professionals who are female, the mean age, mean age squared, mean years of technical experience, and mean years of technical experience squared for the IT workforce, as well as mean size of location and mean size of firm of IT professional employers in the region.

In Tables 9 and 10, I present the results from the regression specified above. Table 9 presents results for the entire sample of states. California is very large, and may dominate the results, so in Table 10, I present results excluding California.

In Specification I of Table 9, I include IT wage-NASDAQ correlation and workforce characteristics as dependent variables. The coefficient on wage correlation is positive and significant at the 10% level. A one-standard deviation increase in wage sensitivity leads to a 2.0 percentage point increase in region-wide options incidence. On average, 40% of IT professionals in a region receive options, so a 2 percentage point increase leads to about an 5% increase in the likelihood of receiving options.

Specification II includes IT employment-NASDAQ correlation and workforce characteristics. The employment sensitivity coefficient is positive and significant at the 5% level. A one-standard deviation increase in employment sensitivity translates to a 2.3 percentage point increase in option rate. At the mean, this translates to about a 5.7% increase in the likelihood of receiving options.

In Specification III, I include both sensitivity measures. The employment correlation measure is significant at the 5% level and the wage correlation measure is not significant. This indicates that the employment effect dominates the wage effect.

I present the results of the same estimations excluding California in Table 10. The coefficients on the wage correlation variable in Specification I and the employment correlation measure in Specification II are of similar magnitude in both samples, although the statistical significance varies. Without California, the wage correlation term in Model I loses any claim of marginal significance while the employment correlation term becomes more significant in Model II. Again, when both terms are included, the employment term dominates the wage term.

As the model detailed above indicates, stock option incidence is positively related to the sensitivity of regional labor markets to industry shocks, particularly shocks that affect regional employment. The region-level results may be biased due to differences in industry and occupation composition of regions. I control for these variables in the next section.

5.2.2 Individual-Level Analysis

I use the Dice.com salary survey data and the correlation measures to estimate a probit model of options incidence. Using individual-level data, I have more degrees of freedom and can control for more individual variation. Using the individual IT data, I estimate the following incidence model:

$$\text{prob}(b_i = 1) = 1 - \Phi(\alpha\eta_j + \beta X_i + c + \epsilon_i)$$

Where b_i is an indicator variable that equals one if individual i receives stock options, η_j is the local labor market-NASDAQ correlation from individual i's region j, X_i is a vector of individual characteristics, and $\Phi(\cdot)$ is a normal cumulative distribution function. X_i includes gender, age, age squared, years of technical experience, years of technical experience squared, location size and firm size, occupation and industry, and IT employment in the region. I adjust standard errors for clustering on regions.

I present the results of the probit estimation in Tables 11 and 12. In Table 11, I present results from three different specifications. In Specification I, I include the IT wage-NASDAQ correlation measure, Specification II includes the IT employment-NASDAQ correlation measure, Specification III includes both measures. In Table 12, I present the coefficients from the industry and occupation dummies from Specification III.

The IT wage-NASDAQ correlation and the IT employment-NASDAQ correlation both contain sampling error that should attenuate estimates of their impact on options incidence. In this analysis I am primarily interested in the sign of the estimates and not the magnitude of the estimates. Although I may lose some significance by not accounting for the sampling error, if I can demonstrate significant results despite the sampling error, I can provide support for the model. In Section 6, I examine the effect of measurement error and sampling error on alternative measures of labor market sensitivity and find that removing the bias due to measurement and sampling error does not affect the significance of results.

In Specification I, IT wage-NASDAQ correlation is positive and significant at the 5% level. The point estimate of the marginal effect at the mean is a 12.5 percentage point increase in options incidence probability given a unit increase in the wage correlation measure. This is an unreasonably large increase in the correlation. The standard deviation of the wage correlation series is 0.215, an increase of one standard deviation increases options incidence probability by about 2.7 percentage points at the mean.

IT employment-NASDAQ correlation is positive and significant at the 10% level in Specification II. The point estimate of the wage correlation coefficient is 0.065. A one standard deviation increase in wage correlation (an increase of 0.326) increases the probability of receiving options by 2.1 points at the mean.

Specification III includes both IT employment-NASDAQ correlation and IT wage-NASDAQ correlation. The coefficient on employment correlation is not significant, but the coefficient on the wage correlation term is positive and significant at the 5% level.

In most specifications the coefficients on the worker characteristics are robust to specification of the local labor market characteristics. I find that women are significantly more likely to receive options than men. Even controlling for occupation and industry effects, the probability that women receive options is 3.0 percentage points higher than men. As seen previously though, women earn approximately 6% less than men, so perhaps women are awarded options as a trade off to higher salary. I find that Age and Age^2 are not significantly related to options incidence, but the coefficient on years of technical experience is positive and significant at the 0.1% level, while technical experience squared is negative and significant at the 1% level. Compared to the mean, ten additional years of experience increase a worker's probability of receiving options by about 9 percentage points (a gain of 16 points from the linear term and a penalty of 7 points from the squared term). Firm size is significant and positively correlated with options incidence, while establishment size is not significant in most specifications.

Tables 12 and 13 include the coefficients on occupation and industry dummies from the probit estimation reported in Specification III of Table 11. The excluded industry is "Computer Software", and the excluded occupation is "Developer: Applications". These two categories are most prevalent in the sample.

The industry and occupation coefficients provide a "common-sense" test of the model. An implication of the model is that the size of an expected shock to an industry is positively related to stock option incidence within that industry[9]. As seen in the table, Internet Services, Telecommunications, Computer Software, and E-Commerce are more likely than the other industries to offer options. Industries least likely to offer options include Non-Profits, Government, Defense, and Agriculture. These values pass the "common-sense" test.

Another implication of the model is that occupations with inelastic supply curves are more likely to receive options. I observe that employees in the following occupations: Strategist, Database Administrator, Systems Developer, and Network Designer, are more likely to be granted options than the excluded occupation, Applications Developer. Occupations less likely to receive options include PC Technician, Web Designer, and Network Manager. Again, these values pass the "common-sense" test.

6 Robustness Checks

In this section, I discuss three potential forms of bias in the estimation. First, I examine sample size bias in the correlation calculations, then I examine the effect of measurement error on the estimation results, and finally, I examine alternative specifications of local labor market - industry shock sensitivity.

6.1 Sample Size Bias in Correlation Estimation

The correlation estimates calculated in Equation 20 may be attenuated by small sample size. To explore the relationship of sample size and correlation estimates, I randomly selected samples of varying size from the CPS-MORG data and calculated the IT labor market correlation using these samples.

Specifically, for a sample of size n, I randomly select n observations (with replacement) from each year, calculate the average wage for each year, and then estimate the Wage-NASDAQ correlation for this sample. I repeat the process for 100 iterations at each n. Figure 1 displays the results. The center line in the figure represents the mean IT Wage-NASDAQ correlation for each set of 100 iterations of sample size n. The upper and lower lines present a 95% confidence interval for the wage correlation estimates. The circles on the figure represent the actual regional correlations used in this paper.

IT Wage-NASDAQ correlation is stable for sample sizes greater than 100. If sample size is less than 100, attenuation is observed. Most of the actual regional correlations have underlying sample sizes above this thresh-hold, so any attenuation due to sample size is negligible.

Figure 2 presents the results of simulating IT Employment-NASDAQ correlations at various sample sizes. I use the same methodology outline above. IT Employment-NASDAQ correlation is slightly biased downward at sample sizes less than 300, with a large amount of attenuation on sample sizes less than 100. There is potential downward bias in the

[9] The relationship of industry characteristics and industry volatility on stock option incidence is explored in Chapter 3

calculations, but the size is small. The actual regional IT Employment-NASDAQ correlations decrease with sample size, so any small sample downward bias would diminish the magnitude of the downward trend, and thus make the final results less significant.

6.2 Errors-in-Variables Correction

Measurement error of the IT employment and IT wage sensitivity to industry shock variables is a potential problem. Measurement error in independent variables in OLS regressions attenuate their associated coefficients. However, I can estimate the signal-to-noise ratio on the poorly measured correlation variables. Using this estimate, I can correct the estimates and standard errors using a modified version of the method presented in Fuller and Hidiroglou (1978) and operationalized in Card and Lemieux (1996). For more details on my implementation of the method, see Appendix A-2.

I present the results from estimating the option incidence rates at the region-level using the full sample and the correlation measures in Table 14. I present three different specification for each measure and I present the estimates adjusted for sampling error as well as the unadjusted estimates.

The reliability of the IT labor market-NASDAQ correlation measures are 0.403 for IT wage-NASDAQ correlation, and 0.750 for IT employment-NASDAQ correlation. Reliability is calculated as:

$$\text{reliability} = 1 - \frac{\text{error variance}}{\text{total variance}}$$

where I bootstrap the error variance on each region's correlation component. The reliabilities of the IT wage-NASDAQ correlation and IT employment-NASDAQ correlations for the sample excluding California are 0.314 and 0.680 respectively. In these specifications, accounting for the poorly measured variables does indeed increase the point estimates, although it does not increase the significance of the estimates.

In Specification A.I of Table 14, the coefficient on IT wage-NASDAQ correlation increases over three-fold. In A.II, the coefficient on IT wage-NASDAQ correlation increases approximately 25%. In A.III the wage-NASDAQ correlation coefficient increases five-fold, while the employment-NASDAQ correlation coefficient decreases substantially. Standard errors increase in all cases.

Repeating the estimations excluding California, I find a similar trade-off. In B.I, the IT wage-NASDAQ correlation coefficient increases by approximately four and a half times. The coefficient on IT employment-NASDAQ correlation increases by about 50% in B.II. In B.III, the IT wage-NASDAQ correlation increases substantially and the IT employment-NASDAQ correlation coefficient is cut in half. All of the point estimate increases come at the cost of larger standard errors.

6.3 Alternative Sensitivity Specifications

The results of the estimation may be sensitive to specification of the labor market sensitivity measure. In this section, I repeat the analysis using several different sensitivity measures: IT labor market-NASDAQ correlations with different lags, the slope of IT labor market series versus NASDAQ series, and the elasticity of IT labor market variables with respect to industry shocks.

In Table 15, I present results from estimating the models presented in Tables 9 to 11 with different measures of IT labor market-industry shock sensitivities. I create the following sensitivity measures, η_j for both average IT wages and average IT employment in each region:

IT labor market-NASDAQ correlation.

I calculate the IT labor market-NASDAQ correlations exactly as specified in Equation 20, except I calculate the correlation of the labor market variables with concurrent NASDAQ levels and NASDAQ levels from two years previous.

IT labor market-NASDAQ slope.

For this measure I estimate the following equation for all states, j:

$$L_{j,t} = \eta_j S_{t-1} + C + u_{j,t}$$

Where L denotes employment, S denotes industry size, j indexes state, and t indexes year.

IT labor market-NASDAQ elasticity.

I develop a measure of elasticity for each state j by estimating the following equation:

$$\log L_{j,t} = \eta_j \log S_{t-1} + C + u_{j,t}$$

Where L denotes employment, S denotes industry size, j indexes state, and t indexes year.

In Table 15, I present results from re-estimating the individual and state-level models presented earlier. Part A of Table 15 recreates the region-level estimation in Table 9, Specification III, and Part B recreates the state-level estimation excluding California in Table 10, Specification III. The alternative correlation measures behave similarly to the base case, while the other measures fail to provide significant results. This is not unexpected because the correlation measures may be less susceptible to outliers than the other measures.

In Part C, I present estimates using the same model as Specification III in Table 11 with the alternative labor market sensitivity variables. The second column, "Correlations with 1 year lag" is the base case presented in Table 11. The results are moderately robust to the alternative measures of correlation, but not robust to the slope and elasticity measures. Although not shown, in specifications of the model that include only one labor market sensitivity (employment sensitivity or wage sensitivity), the coefficient on IT labor market sensitivity to industry shocks is significant.

The basic results of the empirical analysis are moderately robust to choice of local labor market-industry shock sensitivity measure. The correlation between IT labor market outcomes and NASDAQ best captures the variable of interest in the theoretical model, so it is not unexpected that those measures provide the strongest results. There is also weak evidence that the results are robust to sampling error on the sensitivity measures.

7 Discussion

This paper develops and tests a model of the relationship between the sensitivity of local labor market outcomes to industry shocks on the incidence of stock option grants.

I present a simple two-period employment model developed under the assumption that own firm profits are linked to industry growth, and industry growth is in turn linked to outside alternative wages. The primary implication of this model is that stock options can be used to index an employee's wage to her outside alternative wage. Of particular interest is the implication that firms operating in local labor markets where wages and employment are highly sensitive to industry shocks are more likely to offer options to their employees.

The simple current model does not account for uncertainty in future industry shocks, workers' risk preferences, and firm-level strategic behavior. It also operates with the assumption that the sensitivity of local labor markets to industry growth is exogenous to the prevalence of stock options currently in the local labor market. Finally, the model does not attempt to disentwine alternative reasons for stock option grants to employees, such as incentive effects and wage-bill flexibility.

Data from an exclusive survey of Information Technology are presented and bench-marked to demographic data from the Current Population Survey and industry and establishment data from the Bureau of Labor Statistics. The new data matches well to the established data sources and provide additional depth and breadth to current sources of data on Information Technology professionals.

I test the implications of the model using the Information Technology data. The estimates of the relationship between employment sensitivity and stock options are consistent with the model and appear to be moderately robust to alternative specifications and to measurement error.

Alternative explanations for the results include: workers who live in more volatile regions are more risk loving, and thus more likely to demand contingency-based compensation; and in volatile regions, workers may place a higher value on their firm's stock options than the firms themselves - increasing the incentive for firms to offer options as compensation.

Although the model is very simple, it provides straight-forward tools to analyze the implementation of stock option compensation. The IT data support the primary implication of the model that the implementation of stock option compensation is positively related to the sensitivity of local labor markets to industry-wide growth and that stock options are used to insulate worker's wages from regional shocks.

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APPENDIX

A-1 Salary Survey Trimming Methodology

The Dice.com survey is a voluntary on-line survey. In exchange for filling out the survey, respondents receive personalized salary benchmarking information. This information is not valuable to the respondent unless he or she responds accurately. However, due to the nature of on-line surveys, there is an unavoidable amount of noise in the data.

Because there are over 28401 responses, I am able to trim the data aggressively. The goal of trimming the data is to identify and eliminate all surveys that:

1. Do not match my sample frame (e.g. Non-Technical Employees and Part-time workers)
2. Demonstrate obvious inconsistencies (e.g. state of residence and area code of residence are neither consistent or contiguous)
3. Demonstrate highly improbable results (e.g. age less than 18, or salary less than $20,000)

The following table describes the trimming methodology:

Table 1: Trimming Rules

Total Sample Size	Trimmed	Trimming Rule
28401		Number of Initial Responses
28401	-6048	Occupation is Non-Technical or Executive[10]
22353	-3204	State mismatch [11]
19149	-486	Salary is less than $20,000
18663	-28	Salary is greater than $200,000
18635	-325	Not employed full-time
18310	-112	Age is less than 18
18198	-16	Age is greater than 65
18182		Number of Remaining Responses

A-2 Errors-in-Variables Correction

In my estimation methodology, I use a vector of OLS coefficients as an explanatory variable. The estimated coefficients are measured with error and thus attenuate the results of the second stage. I adapt the methodology of Fuller and Hidiroglou (1978) and Card and Lemieux (1996) to eliminate the attenuation bias.

Specifically, I estimate:

$$c_{j,t} = \eta_j \Gamma_t + e_{j,t}$$

where j indexes state, $c_{j,t}$ is the dependent variable, Γ_t is a dependent variable[12] and $e_{j,t}$ is a normally distributed error term. The regression coefficient η_j is measured with error, specifically:

$$\eta_j = \eta_j^* + u_j$$

where η_j^* is the true value, and u_j is an error term distributed $N(0, \sigma^2_{\eta_j})$. Let e_j represent the $T \times 1$ vector of $e_{j,t}$s, where $\sigma^2_{\eta_j}$ is consistently estimated as $\frac{1}{T} e_j' e_j (\Gamma' \Gamma)^{-1}$. Let E be the $JT \times 1$ vector of stacked e_j's.

Let X be the $J \times 1$ vector of η_j's and let X be the dependent variable in a second stage:

$$Y = \beta X + \zeta$$

where X is measured with error:

$$X = X^* + U$$

and,

$$U = \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_J \end{bmatrix}$$

where u_i is distributed $N(0, \sigma^2_{\eta_j})$, and $u_i \perp u_j$ for all i, j.

Note that the OLS estimator for β is not consistent:

$$\begin{aligned} \hat{\beta_{OLS}} &= (X'X)^{-1} X'Y \\ &= ((X^* + U)'(X^* + U))^{-1} (X^* + U)'Y \end{aligned}$$

The probability limit of $\hat{\beta_{OLS}}$ is $(Q^* + U'U)^{-1}(\beta Q^*)$. This is less than the value of the true β, where the attenuation bias is driven by the $U'U$ term.

[12] I focus on the case where Γ_t is one dimensional and there is no weighting, but the methodology generalizes.

In order to eliminate the attenuation bias, I use the Fuller and Hidiroglou (1978) Errors-in-Variables estimator:

$$\widehat{\beta_{OLS}} = (X'X - \widehat{U'U})^{-1}X'Y$$

It suffices to find a consistent estimator of $U'U$. In my specification:

$$U'U = \sum_{j=i}^{J} u_j^2$$

The probability limit of $\frac{U'U}{T}$ is $\sum_{j=i}^{J} \sigma_{\eta_j}^2$. A consistent estimator for $U'U$ is then:

$$\begin{aligned}\widehat{U'U} &= \sum_{j=i}^{J} \frac{1}{T} e_j' e_j (\Gamma'\Gamma)^{-1} \\ &= \frac{1}{T} E'E(\Gamma'\Gamma)^{-1}\end{aligned}$$

In my specification, I use the following Errors-in-Variables estimator:

$$\widehat{\beta_{EIV}} = (X'X - \frac{1}{T} E'E(\Gamma'\Gamma)^{-1})^{-1}X'Y$$

Table 1: Salary Distribution Benchmarking (in $1,000s)

Percentile	Dice	CPS
1%	22	21
5%	30	26
10%	35	29
25%	45	39
50%	60	58
75%	75	75
90%	94	90
95%	105	93
99%	135	140
Mean	61.9	59.3
Variance	591	663

Note: CPS tabulations are for ”Computer Programmers” from the March 2000 CPS. Dice tabulations are from the Dice.com Salary Survey of Information Technology Professionals.

Table 2: Gender Distribution Benchmarking

	Dice Survey		CPS
	Freq.	Percent	Percent
Male	15307	84.19	73.28
Female	2875	15.81	26.72

Note: CPS tabulations are for ”Computer Programmers” from the March 2000 CPS. Dice tabulations are from the Dice.com Salary Survey of Information Technology Professionals.

Table 3: Age Distribution Benchmarking

	Percent		Cumulative	
Age	Dice	CPS	Dice	CPS
18-24	12.33	9.34	12.33	9.34
25-29	29.56	15.27	41.89	24.61
30-39	36.99	40.96	78.88	65.57
40-49	15.83	25.06	94.71	90.63
50-59	4.82	9.22	99.53	99.85
60-64	0.47	0.15	100	100

Note: CPS tabulations are for ”Computer Programmers” from the March 2000 CPS.Dice tabulations are from the Dice.com Salary Survey of Information Technology Professionals.

Table 4: Region Benchmarking

	Sample Size		Distribution		
Regions	Dice	CPS	Dice	CPS	Diff
Maine, New Hampshire, Vermont	118	2214	0.72	1.22	-0.5
Massachusetts (not Boston)	131	1275	0.8	1.14	-0.34
Boston	509	1678	3.12	2.14	0.98
Rhode Island, Connecticut	246	1641	1.51	1.86	-0.35
New York (not New York City)	284	2160	1.74	3.12	-1.38
New York City	840	1357	5.15	2.47	2.68
Southern New Jersey, E. Pennsylvania	768	2185	4.71	3.03	1.68
Northern New Jersey	468	2342	2.87	2.97	-0.1
Western Pennsylvania	216	1250	1.33	1.56	-0.23
Northern Ohio	258	2112	1.58	3.12	-1.54
Southern Ohio, Indiana	300	1687	1.84	2.94	-1.1
Illinois (not Chicago)	88	862	0.54	0.92	-0.38
Chicago	607	2006	3.73	3.25	0.48
Michigan (not Detroit)	84	1266	0.52	1.6	-1.08
Detroit	300	1923	1.84	2.85	-1.01
Wisconsin, Minnesota	384	2017	2.36	4.28	-1.92
Iowa, Missouri, Nebraska	401	2023	2.46	3.05	-0.59
N. Dakota, S. Dakota, Mont., Idaho, Wyo.	58	2590	0.36	0.95	-0.59
Kansas, Oklahoma	222	1569	1.36	1.7	-0.34
Delaware, Maryland	439	1877	2.69	3.08	-0.39
Virginia, Washington D.C.	599	2169	3.68	4.2	-0.52
West Virginia, Kentucky, Tennessee	321	1447	1.97	2.33	-0.36
North Carolina	290	1813	1.78	2.23	-0.45
South Carolina, Georgia, Alabama	585	2418	3.59	5.22	-1.63
Northern Florida	220	1211	1.35	2.22	-0.87
Southern Florida	349	1140	2.14	1.98	0.16
Mississippi, Arkansas, Louisiana	154	1343	0.95	1.84	-0.89
Southern Texas	394	2046	2.42	4.61	-2.19
Northern Texas	660	1334	4.05	3.62	0.43
Washington, Oregon	696	1864	4.27	4.42	-0.15
Colorado	512	1625	3.14	2.38	0.76
New Mexico, Arizona	308	1271	1.89	1.67	0.22
Utah, Nevada	179	1521	1.1	1.12	-0.02
Northern California	2500	3143	15.34	9.56	5.78
Southern California	1770	3112	10.86	4.86	6
Alaska, Hawaii	37	1277	0.23	0.47	-0.24

Note: CPS tabulations are for "Computer Programmers" from the 1992-2001 CPS-MORGS .Dice tabulations are from the Dice.com Salary Survey of Information Technology Professionals. Distributions using the CPS data are weighted, distributions using Dice.com data are unweighted.

Table 5: Establishment Size Distribution Benchmarking

	Percent		Cumulative	
	Dice	BLS	Dice	BLS
< 50	30.09	29.63	30.09	29.63
50-99	15.49	11.43	45.58	41.06
100-499	29.27	35.20	74.84	76.26
500-999	9.51	9.96	84.35	86.22
1000+	15.65	13.78	100	100

Note: BLS tabulations are for "Business Services" from 2000 BLS calculations. Dice tabulations are from the Dice.com Salary Survey of Information Technology Professionals.

Table 6: Dice Sample Means by Region

State	N	%	Salary	Opt	Age	Exp	LocSize	FirmSize
Total Sample	16295		61.88	0.4	32.9	6.35	984	3719
Maine, New Hampshire, Vermont	118	0.72	57.92	0.39	34.46	7.09	640	2654
Massachusetts (not Boston)	131	0.80	58.43	0.34	33.94	6.28	908	3948
Boston	509	3.12	65.92	0.46	32.34	5.54	723	2824
Rhode Island, Connecticut	246	1.51	64.54	0.28	32.25	6.69	1032	4117
New York (not New York City)	284	1.74	56.08	0.33	33.29	6.58	1126	3830
New York City	840	5.15	69.44	0.38	31.66	5.49	991	3238
Southern New Jersey, E. Pennsylvania	768	4.71	62.11	0.34	33.07	6.27	954	3821
Northern New Jersey	468	2.87	66.48	0.38	33.62	5.91	1023	4539
Western Pennsylvania	216	1.33	52.58	0.31	33.51	6.58	738	4025
Northern Ohio	258	1.58	55.63	0.28	33.12	6.77	1357	4433
Southern Ohio, Indiana	300	1.84	54.01	0.32	32.95	7.02	1033	4524
Illinois (not Chicago)	88	0.54	52.89	0.24	32.49	5.82	1680	5132
Chicago	607	3.73	64.29	0.36	32.41	6.13	1131	3998
Michigan (not Detroit)	84	0.52	54.01	0.21	33.19	7.58	976	2711
Detroit	300	1.84	60.08	0.29	32.05	6.62	1035	4514
Wisconsin, Minnesota	384	2.36	58.22	0.33	32.61	6.33	1083	3580
Iowa, Missouri, Nebraska	401	2.46	51.03	0.31	32.43	5.84	1182	4302
NDakota, SDakota, Mont., Idaho, Wyo.	58	0.36	42.14	0.21	31.01	6.08	614	3100
Kansas, Oklahoma	222	1.36	50.87	0.27	33.81	6.46	1235	4540
Delaware, Maryland	439	2.69	60.99	0.34	33.78	6.77	922	3884
Virginia, Washington D.C.	599	3.68	60.58	0.40	32.77	6.28	1031	4108
West Virginia, Kentucky, Tennessee	321	1.97	52.19	0.27	33.49	6.77	988	4131
North Carolina	290	1.78	59.74	0.36	34.92	7.44	1220	4522
South Carolina, Georgia, Alabama	585	3.59	58.94	0.36	33.53	6.52	939	4053
Northern Florida	220	1.35	56.04	0.37	34.99	7.76	1060	4437
Southern Florida	349	2.14	56.66	0.41	32.69	6.62	747	3591
Mississippi, Arkansas, Louisiana	154	0.95	47.67	0.28	34.32	7.07	972	4247
Southern Texas	394	2.42	56.98	0.30	34.31	6.91	1378	4641
Northern Texas	660	4.05	61.01	0.48	33.22	6.49	1423	4583
Washington, Oregon	696	4.27	59.08	0.48	33.37	6.40	1174	3583
Colorado	512	3.14	60.97	0.49	33.65	7.01	1108	4323
New Mexico, Arizona	308	1.89	56.67	0.34	34.37	7.14	1348	4122
Utah, Nevada	179	1.10	53.38	0.46	31.42	5.85	469	3224
Northern California	2500	15.34	72.11	0.58	32.37	6.02	860	2963
Southern California	1770	10.86	61.74	0.41	32.61	6.24	677	2993
Alaska, Hawaii	37	0.23	48.81	0.22	31.24	6.47	211	4496

Notes: Underlying data are from the Dice.com Salary Survey of Information Technology Professionals. "%" is percent of sample, "Salary" is annual salary measured in $1,000s, "Opt" is the percent of workers in the state who receive options, "Age" is average age of respondents, "Exp" is average years of technical experience,"LocSize" is average location size, "FirmSize" is average firm size.

Table 7: Wage Regression for IT Professionals

		Coef	Std. Err
Female	***	-0.0669	(0.0064)
Age	***	0.0231	(0.0018)
Age^2	***	-0.0003	(0.0000)
Experience	***	0.0683	(0.0018)
Experience^2	***	-0.0024	(0.0001)
Location Size (1000s)	***	0.0103	(0.0015)
Firm Size (1000s)	***	0.0067	(0.0008)
Agriculture		-0.032	(0.0237)
Automation		-0.0293	(0.0423)
Bank / Financial / Insurance		-0.0155	(0.0090)
Computer Hardware	***	-0.1175	(0.0103)
Defense	***	-0.1034	(0.0209)
Distributor / Wholesale	***	-0.1187	(0.0230)
Entertainment (movies, games)		-0.0192	(0.0235)
Government	***	-0.1838	(0.0132)
Internet Services	**	0.0242	(0.0079)
Manufacturing	***	-0.1018	(0.0111)
Medical / Pharmaceutical	***	-0.0871	(0.0128)
Non-profit	***	-0.2035	(0.0210)
Publishing	***	-0.1177	(0.0229)
Retail / Mail Order / E-Commerce	**	-0.0481	(0.0148)
Telecommunications	*	-0.0239	(0.0103)
Transportation	***	-0.0857	(0.0201)
Utilities (gas, electricity)		-0.0127	(0.0237)
Other	***	-0.115	(0.0094)
Business Analyst	***	0.1584	(0.0163)
Database Administrator	***	0.1422	(0.0136)
Desktop Support Specialist	***	-0.2229	(0.0141)
Developer: Applications	***	0.1267	(0.0102)
Developer: Client/Server	***	0.1373	(0.0127)
Developer: Database	***	0.0932	(0.0171)
Developer: Systems	***	0.194	(0.0183)
Graphic Designer	***	-0.1449	(0.0271)
Strategist or Architect (IT Management)	***	0.3024	(0.0140)
Mainframe Systems Analyst		-0.0209	(0.0301)
Mainframe Systems Programmer		0.0355	(0.0286)
MIS Manager	***	0.1214	(0.0147)
Multimedia Designer		-0.0655	(0.0480)
Multimedia Manager		0.0892	(0.0592)
Network Design	***	0.2195	(0.0327)
Network Engineer	***	0.0396	(0.0106)
Network Manager		-0.0116	(0.0145)
PC Technician	***	-0.2999	(0.0153)
Project Manager	***	0.1911	(0.0124)
Quality Assurance (QA) Tester		0.0032	(0.0156)
Security Analyst	***	0.14	(0.0299)
Software Engineers	***	0.1772	(0.0116)
Telecommunications Engineer	**	-0.0758	(0.0248)
WAN Specialist		0.0598	(0.0427)
Web Administrator		-0.0373	(0.0280)
Web Designer	**	-0.0726	(0.0209)
Web Developer/Programmer	***	0.1065	(0.0118)
Systems Administrator	*	0.0246	(0.0105)
Region Effects?		Yes	
Constant	***	2.7125	(0.0325)
N		15988	
R^2		0.6031	

Notes: Underlying data are from the Dice.com Salary Survey of Information Technology Professionals. Standard Errors are in parentheses. Omitted industry is "Computer Software", omitted occupation is "Computer Analyst".
*** denotes significance at the 0.1% level, ** denotes significance at the 1% level, * denotes significance at the 5% level.

Table 8: IT Labor Market Outcomes-NASDAQ Correlations (by region)

IT wage-NASDAQ Correlation		IT Employment-NASDAQ Correlation	
Iowa, Missouri, Nebraska	0.937	Virginia, Washington D.C.	0.949
Colorado	0.923	Washington, Oregon	0.923
Wisconsin, Minnesota	0.899	Utah, Nevada	0.915
Washington, Oregon	0.893	Northern California	0.906
Maine, New Hampshire, Vermont	0.890	Wisconsin, Minnesota	0.902
Northern California	0.885	Northern New Jersey	0.888
New York (not New York City)	0.878	Iowa, Missouri, Nebraska	0.874
Boston	0.851	N. Dakota, S. Dakota, Mont., Idaho, Wyo.	0.847
Northern Texas	0.833	Northern Texas	0.825
Rhode Island, Connecticut	0.786	Chicago	0.822
Northern New Jersey	0.762	Colorado	0.811
Southern Ohio, Indiana	0.727	Southern New Jersey, E. Pennsylvania	0.786
Detroit	0.723	Southern Florida	0.778
Chicago	0.716	Northern Florida	0.764
New York City	0.713	North Carolina	0.759
West Virginia, Kentucky, Tennessee	0.709	South Carolina, Georgia, Alabama	0.754
Mississippi, Arkansas, Louisiana	0.693	Mississippi, Arkansas, Louisiana	0.747
Southern Texas	0.687	Maine, New Hampshire, Vermont	0.740
Southern New Jersey, E. Pennsylvania	0.682	Delaware, Maryland	0.712
Utah, Nevada	0.679	Boston	0.706
Southern Florida	0.672	Southern Texas	0.696
Northern Ohio	0.651	Detroit	0.694
Kansas, Oklahoma	0.648	New Mexico, Arizona	0.670
Michigan (not Detroit)	0.646	New York City	0.666
Delaware, Maryland	0.610	Northern Ohio	0.646
Southern California	0.602	Kansas, Oklahoma	0.583
Western Pennsylvania	0.497	West Virginia, Kentucky, Tennessee	0.568
Northern Florida	0.462	Michigan (not Detroit)	0.524
North Carolina	0.427	Southern Ohio, Indiana	0.506
South Carolina, Georgia, Alabama	0.424	New York (not New York City)	0.271
Virginia, Washington D.C.	0.333	Alaska, Hawaii	0.132
Massachusetts (not Boston)	0.218	Rhode Island, Connecticut	-0.047
New Mexico, Arizona	0.198	Southern California	-0.102
Illinois (not Chicago)	0.024	Western Pennsylvania	-0.194
N. Dakota, S. Dakota, Mont., Idaho, Wyo.	-0.006	Massachusetts (not Boston)	-0.236
Alaska, Hawaii	-0.111	Illinois (not Chicago)	-0.554

Notes: Calculations are correlations of mean IT employment and mean IT wages calculated annually (1993-2001) with mean NASDAQ from the previous year. The mean and standard deviation for each column are weighted by state IT employment.

Table 9: The Relationship of IT Labor Market-NASDAQ Correlations and Options Incidence (region-level)

	I		II		III	
Wage Corr.	0.104	†			0.071	
	(0.058)				(0.059)	
Emp. Corr.			0.073	*	0.060	*
			(0.027)		(0.027)	
Age	0.028		0.025		0.027	
	(0.018)		(0.018)		(0.018)	
Exp	-0.065		-0.065		-0.064	
	(0.038)		(0.039)		(0.039)	
Est. Size	0.001		0.015		-0.006	
	(0.071)		(0.070)		(0.071)	
Firm Size	-0.062		-0.074		-0.063	
	(0.039)		(0.036)		(0.038)	
Female	0.603		0.479		0.456	
	(0.499)		(0.424)		(0.428)	
Constant	-0.062		0.120		-0.002	
	(0.486)		(0.476)		(0.492)	
N	36		36		36	
R^2	0.4382		0.4593		0.481	

Notes: Each observation represents a region. The dependent variable is percentage of workers in the state. States are weighted by their mean IT employment across the time frame. Standard errors are in parentheses. Abbreviations: *Emp. Corr.* denotes the correlation between IT Employment and NASDAQ for the region of the observation, *Wage Corr.* denotes the correlation between IT Wages and NASDAQ for the region of the observation, *Age* is mean age, *Exp* is mean years of technical experience, *Est. Size* is mean establishment size, *Firm Size* is mean firm size.
*** indicates significance at the .1% level, ** indicates significance at the 1% level, * indicates significance at the 5% level, † indicates significance at the 10% level.

Table 10: The Relationship of IT Labor Market-NASDAQ Correlations and Options Incidence (region-level, excluding CA)

	I		II		III	
Wage Corr.	0.087				0.054	
	(0.057)				(0.052)	
Emp. Corr.			0.090	**	0.079	**
			(0.026)		(0.025)	
Age	0.034	*	0.029	*	0.031	*
	(0.014)		(0.014)		(0.014)	
Exp	-0.059	*	-0.057	*	-0.057	*
	(0.028)		(0.027)		(0.027)	
Est. Size	-0.021		-0.003		-0.019	
	(0.067)		(0.064)		(0.062)	
Firm Size	-0.020		-0.021		-0.013	
	(0.031)		(0.028)		(0.029)	
Female	0.090		-0.031		-0.039	
	(0.405)		(0.300)		(0.325)	
Constant	-0.359		-0.221		-0.306	
	0.401		0.371		0.398	
N	34		34		34	
R^2	0.2326		0.3138		0.3382	

Notes: Each observation represents a region. The dependent variable is percentage of workers in the state. States are weighted by their mean IT employment across the time frame. Standard errors are in parentheses. Abbreviations: *Emp. Corr.* denotes the correlation between IT Employment and NASDAQ for the region of the observation, *Wage Corr.* denotes the correlation between IT Wages and NASDAQ for the region of the observation, *Age* is mean age, *Exp* is mean years of technical experience, *Est. Size* is mean establishment size, *Firm Size* is mean firm size.
*** indicates significance at the .1% level, ** indicates significance at the 1% level, * indicates significance at the 5% level.

Table 11: The Relationship of IT Labor Market-NASDAQ Correlations and Options Incidence

	mean	I		II		III	
Wage Corr.	0.672	0.125	*			0.100	*
		(2.272)				(2.177)	
Emp. Corr.	0.635			0.065	†	0.043	
				(1.652)		(1.297)	
Age	37.422	-0.005		-0.005		-0.005	
		(-1.546)		(-1.479)		(-1.509)	
Age^2 (100s)	15.008	0.004		0.004		0.004	
		(0.816)		(0.741)		(0.781)	
Exp	7.989	0.016	***	0.016	***	0.016	***
		(4.088)		(4.088)		(4.087)	
Exp^2 (100s)	0.978	-0.066	**	-0.066	**	-0.066	**
		(-2.765)		(-2.775)		(-2.766)	
Est. Size (1000s)	1091	0.003		0.003		0.003	
		(1.049)		(1.050)		(1.030)	
Firm Size (1,000s)	4096	0.011	***	0.011	***	0.011	***
		(4.369)		(4.252)		(4.355)	
Female	0.186	0.031	*	0.030	*	0.030	*
		(2.543)		(2.456)		(2.480)	
Occ Dummies?		Y		Y		Y	
Ind Dummies?		Y		Y		Y	
Pseudo R^2		0.1103		0.1097		0.1109	
N		16295		16295		16295	

Notes: The dependent variable is an options incidence indicator. Coefficients are marginal effects on options probability calculated at the mean. T-stats are in parentheses. *** indicates significance at the .1% level, ** indicates significance at the 1% level, * indicates significance at the 5% level, † indicates significance at the 10% level. Standard errors are adjusted for clustering in regions.

Abbreviations: *Emp. Corr.* denotes the correlation between IT Employment and NASDAQ for the region of the observation, *Wage Corr.* denotes the correlation between IT Wages and NASDAQ for the region of the observation, *Exp* is years of technical experience, *Est. Size* is the size of the establishment of employment, *Firm Size* is the size of the firm of employment, *Occ Dummies* and *Ind Dummies* indicate the presence of occupation and industry dummies.

Table 12: Industry Coefficients (From Table 11.III)

	Mean	dF/dx		T-stat
Industry				
Agriculture	0.012	-0.184	***	(-4.887)
Automation	0.004	-0.215	**	(-3.025)
Bank / Financial / Insurance	0.092	-0.082	***	(-4.290)
Computer Hardware	0.067	-0.038		(-1.587)
Defense	0.017	-0.188	***	(-4.612)
Distributor / Wholesale	0.013	-0.188	***	(-4.327)
Entertainment (movies, games)	0.007	-0.054		(-0.856)
Government	0.059	-0.306	***	(-12.299)
Internet Services	0.091	0.246	***	(12.837)
Manufacturing	0.080	-0.147	***	(-7.143)
Medical / Pharmaceutical	0.042	-0.188	***	(-6.901)
Non-profit	0.015	-0.326	***	(-9.527)
Publishing	0.010	-0.177	***	(-4.122)
Retail / Mail Order / E-Commerce	0.027	-0.020		(-0.592)
Telecommunications	0.067	0.147	***	(5.455)
Transportation	0.017	-0.199	***	(-4.457)
Utilities (gas, electricity)	0.015	-0.138	**	(-3.373)
Other	0.092	-0.199	***	(-13.997)

Notes: The reported coefficients are from the Industry dummies suppressed from Table 11.III. Coefficients are marginal effects on options probability calculated at the mean. T-stats are in parentheses.
*** indicates significance at the .1% level, ** indicates significance at the 1% level, * indicates significance at the 5% level. Standard errors are adjusted for clustering on states. The excluded industry is "Computer Software".

Table 13: Occupation Coefficients (From Table 11.III)

Occupation	Mean	dF/dx		T-stat
Computer Analyst	0.114	0.044		(1.987)
Business Analyst	0.025	0.036		(1.068)
Database Administrator	0.043	0.126	***	(4.327)
Desktop Support Specialist	0.035	0.063		(2.111)
Developer: Client/Server	0.045	0.037		(1.732)
Developer: Database	0.021	0.047		(1.138)
Developer: Systems	0.018	0.127	***	(3.858)
Graphic Designer	0.007	0.008		(0.141)
Strategist or Architect (IT Management)	0.040	0.158	***	(6.110)
Mainframe Systems Analyst	0.011	-0.042		(-0.732)
Mainframe Systems Programmer	0.010	0.007		(0.106)
MIS Manager	0.040	0.038		(1.201)
Multimedia Designer	0.002	0.192		(1.786)
Multimedia Manager	0.001	-0.150		(-2.248)
Network Design	0.004	0.245	**	(2.634)
Network Engineer	0.083	0.024		(1.103)
Network Manager	0.041	-0.022	**	(-0.595)
PC Technician	0.034	-0.048	***	(-1.559)
Project Manager	0.060	0.137	***	(4.281)
Quality Assurance (QA) Tester	0.022	0.154	***	(4.369)
Security Analyst	0.007	0.054		(1.119)
Software Engineers	0.059	0.151	***	(6.103)
Telecommunications Engineer	0.010	-0.045	*	(-1.063)
WAN Specialist	0.003	-0.020		(-0.234)
Web Administrator	0.007	-0.046		(-0.670)
Web Designer	0.014	-0.024	**	(-0.430)
Web Developer/Programmer	0.052	0.059		(2.474)
Systems Administrator	0.092	0.037		(1.724)

Notes: The reported coefficients are from the Occupation dummies suppressed from Table 11.III. Coefficients are marginal effects on options probability calculated at the mean. T-stats are in parentheses.
*** indicates significance at the .1% level, ** indicates significance at the 1% level, * indicates significance at the 5% level. Standard errors are adjusted for clustering on states. The excluded occupation is "Developer: Applications".

Table 14: The Relationship of IT Labor Market-Industry Shock Sensitivity and Options Incidence - Adjusted for Measurement Error

A. Region-Level Analysis

	I		II		III	
	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted
Wage Corr. (r = 0.403)	0.104	0.373 †			0.071	0.368
	(0.064)	(0.200)			(0.066)	(0.410)
Emp. Corr. (r = 0.750)			0.073 †	0.101 †	0.060	0.003
			(0.037)	(0.050)	(0.039)	(0.125)
Age	0.028	0.034	0.025	0.025	0.027	0.034
	(0.024)	(0.021)	(0.023)	(0.023)	(0.023)	(0.024)
Exp	-0.065	-0.060	-0.065 †	-0.065 †	-0.064 †	-0.060 †
	(0.038)	(0.034)	(0.038)	(0.037)	(0.038)	(0.035)
Est. Size	0.001	-0.097	0.015	0.006	-0.006	-0.096
	(0.080)	(0.099)	(0.076)	(0.075)	(0.078)	(0.132)
Firm Size	-0.062 †	-0.016	-0.074 *	-0.071 *	-0.063 †	-0.016
	(0.032)	(0.043)	(0.029)	(0.029)	(0.031)	(0.066)
Female	0.603	0.359	0.479	0.397	0.456	0.356
	(0.467)	(0.443)	(0.468)	(0.467)	(0.467)	(0.435)
Constant	-0.062	-0.519	0.120	0.122	-0.002	-0.510
	(0.611)	(0.625)	(0.590)	(0.575)	(0.599)	(0.884)
N	36	36	36	36	36	36
R^2	0.4382	0.5721	0.4593	0.4869	0.481	0.5721

B. Region-Level Analysis, excluding CA

	I		II		III	
	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted
Wage Corr. (r = 0.314)	0.087	0.384 †			0.054	0.318
	(0.055)	(0.203)			(0.055)	(0.491)
Emp. Corr. (r = .680)			0.090 *	0.137 *	0.079 †	0.036
			(0.037)	(0.053)	(0.039)	(0.172)
Age	0.034	0.039 *	0.029	0.028	0.031	0.037
	(0.020)	(0.017)	(0.019)	(0.018)	(0.019)	(0.022)
Exp	-0.059 †	-0.053 †	-0.057	-0.055 †	-0.057 †	-0.053
	(0.033)	(0.028)	(0.031)	(0.029)	(0.031)	(0.028)
Est. Size	-0.021	-0.117	-0.003	-0.008	-0.019	-0.099
	(0.069)	(0.086)	(0.063)	(0.060)	(0.065)	(0.151)
Firm Size	-0.020	0.029	-0.021	-0.014	-0.013	0.024
	(0.030)	(0.041)	(0.028)	(0.027)	(0.029)	(0.062)
Female	0.090	-0.071	-0.031	-0.120	-0.039	-0.102
	(0.428)	(0.370)	(0.409)	(0.392)	(0.410)	(0.372)
Constant	-0.359	-0.830	-0.221	-0.220	-0.306	-0.725
	(0.530)	(0.539)	(0.495)	(0.465)	(0.503)	(0.894)
N	34	34	34	34	34	34
R^2	0.2326	0.473	0.3138	0.3931	0.3382	0.4792

Notes: Part A recreates Table 9, and Part B recreates Table 10. Each observation represents a region. The dependent variable is the percentage of workers in the region that hold options. The "Unadjusted" column displays the point estimates and non-robust standard errors, the "Adjusted" column displays estimates adjusted for measurement error. Standard errors are in parentheses. Reliability measures of poorly measured variables are in parentheses next to the variable name.

Abbreviations: *Wage Corr.* denotes the correlation between IT Wages and NASDAQ for the region of the observation, *Emp. Corr.* denotes the correlation between IT Employment and NASDAQ for the region of the observation, *Age* is mean age, *Exp* is mean years of technical experience, *Est. Size* is mean establishment size, *Firm Size* is mean firm size.

* indicates significance at the 5% level, † indicates significance at the 10% level.

Table 15: The Relationship of Various Measures of IT Labor Market-Industry Shock Sensitivity and Options Incidence

A. Option Incidence Rates (by region)

	Correlations			Slope	Elasticity
	0 Lag	1 Year Lag	2 Year Lag	1 Year Lag	1 Year Lag
Wage Sens.	0.079	0.071	0.081	0.007	0.006
	(0.061)	(0.059)	(0.075)	(0.023)	(0.024)
Emp.Sens.	0.038 †	0.060 *	0.081 *	-0.007	-0.008
	(0.022)	(0.027)	(0.034)	(0.020)	(0.021)
R^2	0.4629	0.4810	0.5059	0.3894	0.3899
N	36	36	36	36	36

B. Option Incidence Rates (by region, excluding CA)

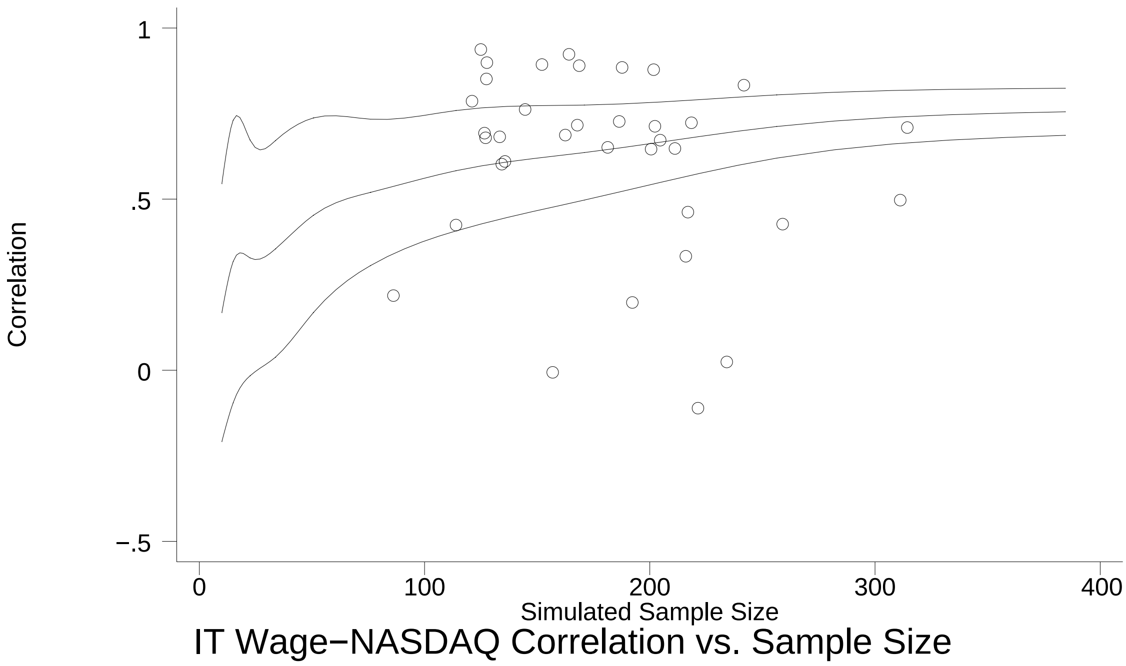
	Correlations			Slope	Elasticity
	0 Lag	1 Year Lag	2 Year Lag	1 Year Lag	1 Year Lag
Wage Sens.	0.053	0.054	0.063	0.017	0.010
	(0.053)	(0.052)	(0.064)	(0.020)	(0.020)
Emp.Sens.	0.056 *	0.079 **	0.098 **	-0.001	0.002
	(0.020)	(0.025)	(0.032)	(0.017)	(0.021)
R^2	0.2930	0.3382	0.3782	0.2040	0.1849
N	34	34	34	34	34

C. Option Incidence (by individuals)

	Correlations			Slope	Elasticity
	0 Lag	1 Year Lag	2 Year Lag	1 Year Lag	1 Year Lag
Wage Sens.	0.090 †	0.100 *	0.084	0.005	0.003
	(1.853)	(2.177)	(1.532)	(0.262)	(0.164)
Emp.Sens.	0.020	0.043	0.077 *	-0.003	-0.004
	(0.729)	(1.297)	(1.989)	(-0.253)	(-0.366)
R^2	0.1099	0.1109	0.1114	0.1082	0.1082
N	16295	16295	16295	16295	16295

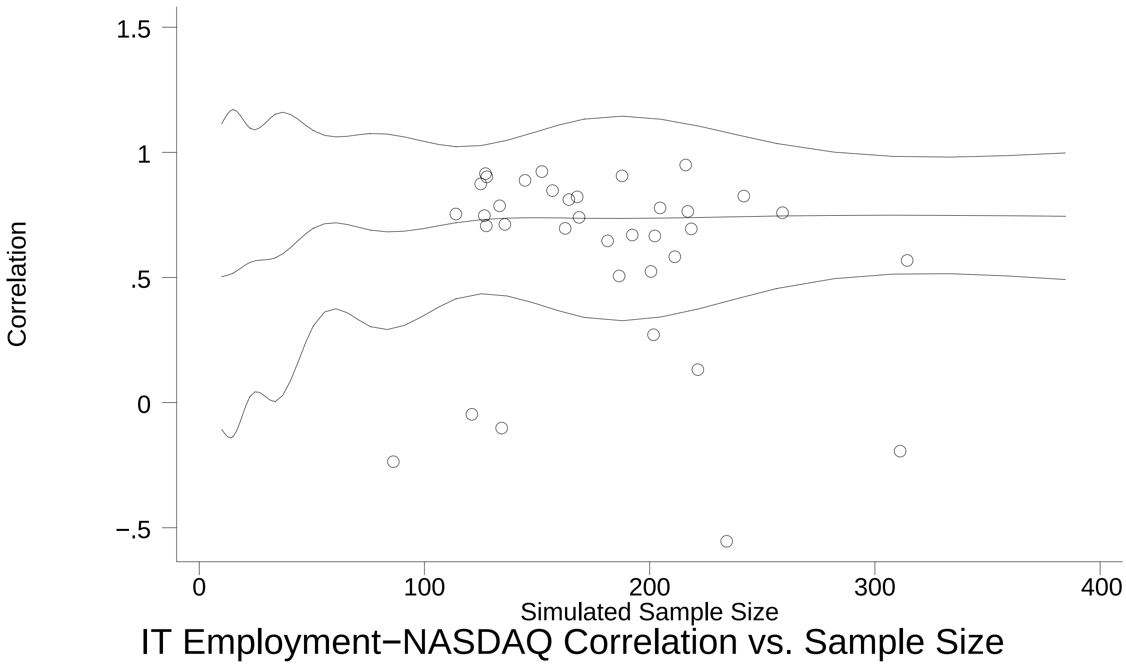
Notes: "Correlations" denote correlation of yearly cells of IT Employment and Wages with NASDAQ by state. "Slope" indicates the estimated slope of annual IT employment and wages versus NASDAQ by region. "Elasticity" indicates the estimated slope of log(IT employment) and log(IT wages) versus log(NASDAQ) by region.
Part A, B - These parts re-estimate the models in Table 9:III and Table 10:III, respectively . Each observation represents a region. The dependent variable is rate of options incidence within IT employment in the region. Standard errors are in parentheses.
Part C - This part re-estimates the model in Table 11:III. Observations are individuals. The dependent variable is an options incidence indicator. Coefficients are marginal effects on options probability calculated at the mean. T-stats are in parentheses. Standard errors are adjusted for clustering on regions.
*** indicates significance at .1%, ** indicates significance at 1%, * indicates significance at 5% level.
Abbreviations: *Emp. Sens.* denotes the measure of IT employment sensitivity to industry shocks employed in the model, *Wage Sens.* denotes the measure of IT wage sensitivity employed in the model.

Figure 1: IT Wage Correlation and Sample Size



Notes: Center line represents simulated IT Wage-NASDAQ Correlation for the U.S. according to sample size. Outer lines indicate +/- 2 standard deviations. Circles indicate Correlation Estimates for each region.

Figure 2: IT Employment Correlation and Sample Size



Notes: Center line represents simulated IT Employment-NASDAQ Correlation for the U.S. according to sample size. Outer lines indicate +/- 2 standard deviations. Circles indicate Correlation Estimates for each region.