Job Security *Does* Affect Economic Efficiency: Theory, A New Statistic, and Evidence from Chile *

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Abstract

The extensive empirical macro- and micro-level evidence on the impact of job security provisions is largely inconclusive. We argue that the weak evidence is a consequence of the weak power of statistics used, which is suggested by a dynamic theory of plant-level labor demand that we develop. This model speaks clearly on one issue: firing costs drive a wedge between the marginal revenue product of labor and its marginal cost. We examine changes in this gap as our test statistic. It is easy to compute and has a welfare interpretation. We use census data of Chilean manufacturing firms for the years 1979-1996 to look for real effects induced by two significant increases in the costs of dismissing employees. Similar to previous findings in other data, the traditional labor demand statistics provide little evidence of a negative impact from increases in firing costs. While we find no evidence that gaps increase for inputs that are not directly affected by firing costs, we find large and statistically significant increases in the mean and variance of the within-firm gap between the marginal revenue product of labor and the wage for both blue and white collar workers.

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1 Introduction

Job security regulations that increase the costs of dismissing employees are pervasive around the world, as summarized in Figure 1. The 2006 riots in France, which ensued after an attempt to lower firing costs, show that they remain a matter of intense debate. Lazear (1990) proves that the distortion introduced by these provisions can be completely undone by efficient contracts, where the mandated firing costs are passed on to workers who willingly accept a lower wage. A wide body of empirical work that investigates their impact using both macro- and micro-level data has followed, much of which is summarized in Addison and Teixeira (2001) and in Heckman and Pages (2004).[1] In our view, the wide disparity of reported findings provide no clear evidence that firing costs have a negative economic impact.

We argue that the mixed evidence is a consequence of the weak power of the statistics being used. Researchers have examined how changes in job security change aggregate employment and unemployment, micro- and aggregate- estimates of labor demand, the probability of adjustment, and the size of adjustment conditional on adjusting. All of these statistics are fundamentally based on the plant-level labor demand equations, which our theory suggests may be a difficult object to identify or estimate in the presence of firing costs.[2] Also, while unobserved variables are always a potential problem, the theory points directly to how they can weaken the tests based on labor demand, if not destroy their econometric validity. We argue that job security provisions do have real effects and low (or perhaps no) power is the culprit in the reported ambiguous findings.

The model is clear on one issue: firing costs drive a wedge between the marginal revenue product of labor and its marginal cost (wage). This idea has been widely explored in the literature analyzing the nature of labor adjustment costs (see the review in Bond and Van Reenen (2003)).[3] We develop a new test statistic, showing how to directly estimate the difference between the marginal revenue product and the marginal input price using plant-level data. Our approach is robust to many of

[1] A large body of theoretical work has also followed. Depending upon the assumptions, some theory papers find a positive effect of increasing firing costs on employment (Bentolila and Bertola (1990), Alvarez and Veracierto (2001)), while others find a negative effect (Risager and Sorensen (1997), Bertola (1990), and Hopenhayn and Rogerson (1993)).

[2] Sargent (1978) is the classic work on estimation of dynamic labor demand. Shapiro (1986) uses the Euler equations to recover dynamic demand for labor and capital.

[3] Perhaps closest to this work are the ideas regarding adjustment costs developed in Caballero and Engel (1993) and Caballero and Engel (1999), who demonstrate the existence of fixed costs of adjustment by forecasting the optimal level of capital for plants, and then showing that the probability of adjustment is increasing in the difference between this optimal level and the observed level of capital. Cooper and Willis (2001) and Cooper and Willis (2003) challenge this approach, arguing that it is very sensitive to the modeling choice for calculating optimal capital. On the gaps see also Gali, Gertler, and Lopez-Salido (2002), Caballero, Cowan, Engel and Micco (2004), and Eslava, Haltiwanger, Kugler, and Kugler (2006).

the problems that we show can afflict the more traditional statistics. It is easy to compute, in our data has significant power, and from the social planner's perspective, has a clear link to welfare, as increases in the absolute value of the gap are associated with greater economic inefficiency.

Another advantage of this approach is the wide variety of specification checks available, one for each of the freely adjustable inputs. While firing costs will affect the demand for inputs that are easily adjusted, like materials and electricity, optimization implies that they should not increase the gaps for freely adjustable inputs. We use these gaps as "control" gaps. They tell us whether increases in the labor gaps - if found - might be related to some other unobserved phenomenon that affects the gaps of all inputs.

Using plant-level census data for Chilean manufacturing firms for the years 1979-1996, we look for real effects induced by two significant increases in job security. The first change, in late 1984, no longer exempted from severance pay firms that could show "economic cause" for dismissal. Severance was set equal to no less than a month's wages per year of tenure, with a five month ceiling. The second change, in 1991, increased the ceiling to 11 months, and added a 20% surcharge if the employer could not prove "economic cause." Both Edwards and Edwards (2000), who use aggregate time-series data, and Pages and Montenegro (1999), who use individual-level employment survey data, find *no* effect of these increases on aggregate unemployment levels, although the latter study does report that the young workers and the women tend to lose to the older men.

Using production function estimates from a variety of estimators, for both blue and white collar workers we find significant and substantial increases in both the mean and the variance of *within-firm* gaps in response to increases in firing costs. The timing of the increases in the gaps is linked to the timing of the increases in firing costs. After the deep recession in 1982-83, which reduced both the mean and the variance of the gap substantially, these moments are relatively unchanged until they sharply increase right after the first increase in firing costs. They continue to increase until 1987, and then level off until 1990. Then, the second increase in firing costs leads immediately to an increase again in both the mean and variance of the gaps. Almost all years after 1984 have average gaps that are significantly different from the 1984 gap, and all years have a variance that is significantly different from the 1984 variance. Finally, we find no evidence that either the materials or the electricity gaps increase in either their mean or variance.

We then turn to the question of what we would find if we used the usual statistics, all of which are fundamentally based on plant-level dynamic labor demand. As reported above, two studies have found no effects on aggregate unemployment. We use the *plant-level* variation to estimate the labor demand equations using ordinary least squares (OLS), a fixed effects estimator, and the Blundell and Bond (1998) instrumental variables (IV) estimator. We find no evidence that the level of demand falls nor do we find that the sensitivity to the wage systematically changes. We also look at the coefficient on lagged labor, which is often expected to move toward "1" as firing costs increase. While the IV estimates are consistent with this prediction when all parameters of the demand function are allowed to freely vary across the three periods, neither the OLS nor the fixed effects estimators display a similar pattern.

We estimate changes in the probability of plant-level adjustment in response to job security, which conventional intuition suggests should fall as firing costs increase. Our theory says this probability may not necessarily fall across all increases in firing costs. In our data, with no controls the probability of adjustment *increases* from 82% to 86% as firing costs increase, and it remains increasing until we condition on plant-level productivity and wage, lagged labor, and aggregate control factors.

We also look at whether the number of hires or fires, conditional on adjusting, is attenuated toward zero, which intuition also suggests. Number of employees fired is attenuated toward zero as firing costs increase, but the number of hires is *increasing* in firing costs. These mixed results for the adjustment statistics are consistent with the mixed results from the direct estimates of labor demand, as these statistics are all functions of the labor demand function.

We also develop one additional statistic that is implied by the Lazear (1990) insight. We calculate the implied wage change necessary to undo the distortion of the job security legislation under several different scenarios. The actual change in the average wage after the first dose of job security is several magnitudes larger than what is necessary to offset the firing cost. There is no change in average wage after the second dose. This new statistic also appears to be inconclusive in this Chilean data.

We conclude the traditional evidence on whether firing costs have real economic effects is inconclusive, both in our data and across the wide body of empirical work in this area. In contrast, our gap statistic points to significant economic distortions arising from firing costs.

The paper is organized as follows. Section 2 develops the theory. Section 3 introduces the new gap statistic. Section 4 summarizes the key economic reforms in Chile over the period that we examine (1979-1996). Section 5 describes the plant-level data. Section 6 describes the estimation approach, and Section 7 reports the evidence from the gap. Section 8 presents the traditional statistics, and Section 9 concludes.

2 Theory of Labor Demand with Firing Costs

We derive labor demand as the solution to an infinite-horizon problem for the firm that faces firing costs.[4] The main results are as follows. Without firing costs, firms respond to plant-level productivity and wage shocks by choosing a level of labor that equates per-period marginal revenue with the wage. The inefficiencies introduced by firing costs can be undone by efficient contracts. When not undone, the solution to the profit maximization problem may not be unique, invalidating standard econometric arguments necessary to motivate estimation of a labor demand equation. When labor demand is single-valued (that is, a function), it is an implicit one and is not generally linear in its arguments, potentially requiring weaker-powered non-parametric tests. Finally, the theory does not agree with the common intuition that the probability of adjusting is monotonically decreasing in firing costs, and that hiring and firing conditional on adjusting is attenuated toward zero as firing costs increase.

All of these findings may help to explain the lack of evidence on a negative impact of firing costs despite the many empirical studies investigating the question. Readers not interested in the technical details underlying these results can skip to Section 3 for a discussion of our gap test and Section 7 for the results.

2.1 The Infinite Horizon Model

We assume output at time t is given by the production function

$$Q(l_t, \theta_t) = \theta_t f(l_t)$$

which has a single input labor, with $f(l_t)$ increasing and concave and with productivity (or demand) shock θ_t. Wages are exogenously set at w_t per unit of labor. In each period θ_t and w_t are realized before the labor decision is made for that period. With no firing costs, the profit function for the firm is:

$$\pi_t = \theta_t f(l_t) - w_t l_t, \tag{1}$$

[4] Caplin and Krishna (1986) develop an early infinite-horizon labor demand models that is similar along some dimensions to this model.

and the optimal choice of labor in each period t equates marginal revenue with marginal cost:

$$f'(l_t^*) = \frac{w_t}{\theta_t}. \tag{2}$$

The firm fires in period t if $\frac{w_t}{\theta_t}$ is greater than $\frac{w_{t-1}}{\theta_{t-1}}$, and hires if $\frac{w_t}{\theta_t}$ is less than $\frac{w_{t-1}}{\theta_{t-1}}$.[5]

With firing costs, per-period profits in period t are given by current profits π_t minus the costs associated with adjusting labor:

$$\begin{aligned} & \pi(\theta_t, w_t, l_t) && - && C(l_t - l_{t-1}; F, c) \\ = \; & \theta_t f(l_t) - w_t l_t && - && C(l_t - l_{t-1}; F, c), \end{aligned} \tag{3}$$

where

$$C(l_t - l_{t-1}; F, c) = \begin{cases} F + c * |l_t - l_{t-1}| & \text{if } l_t < l_{t-1} \\ 0 & \text{if } l_t \geq l_{t-1} \end{cases} \tag{4}$$

The per-unit labor cost of firing we denote c.[6] We write it as linear in workers because this is way the cost enters the firm problem in Chile and many other countries. There is also evidence of non-convex adjustment costs for labor (e.g. Hamermesh (1989), Pfann and Palm (1993), and Cooper, Haltiwanger, and Willis (2004)). We include a fixed cost F of adjustment to allow for this possibility.

At time t, given l_{t-1}, the expected discounted profits for any given sequence of future labor levels $\{l_s\}_{s=t}^{\infty}$ is

$$\pi(\theta_t, w_t, l_t) - C(l_t - l_{t-1}) + E_t[\sum_{s=t+1}^{\infty} \beta^{s-t}(\pi(\theta_s, w_s, l_s) - C(l_s - l_{s-1}))], \tag{5}$$

with $\beta < 1$ denoting the discount rate and E_t denoting the expectation conditional on the information available at time t, and (F, c) suppressed throughout. The uncertainty about the future arises because (θ_t, w_t) evolve probabilistically. We assume they follow a first order Markov process, and we write the transition probability function as $dP(\theta', w'|\theta, w)$.[7] The firm observes (θ_t, w_t) before choosing l_t. With (θ_t, w_t) known, beliefs about probabilities associated with any sequence of outcomes $\{\theta_s, w_s\}_{s=t+1}^{\infty}$ determine the expected value of any contingency plan $\{l_s\}_{s=t+1}^{\infty}$.

It will be useful for our analysis to consider the recursive value-function representation:[8]

$$V(\theta_t, w_t, l_{t-1}) = max_l \; \theta_t f(l) - w_t l - C(l - l_{t-1}) + \beta \overline{V}(\theta_t, w_t, l), \tag{6}$$

[5] We abstract from the entry/exit decision because the main issues can be illustrated without adding this complication.

[6] We abstract from differences in severance payments that arise from differences in tenure of employees because we do not observe matched employer-employee data.

[7] It is straightforward to allow the conditional distribution of θ to be higher order Markov.

[8] Standard regularity conditions must hold to ensure the solution to this functional equation is the same as the solution to maximizing the sequential problem in (5). See Stokey and Lucas (1993).

where $V(\theta_t, w_t, l_{t-1})$ is the expected discounted profits at time t, and the continuation value of being at (θ_t, w_t, l) is

$$\overline{V}(\theta_t, w_t, l) = \int_{\theta', w'} V(\theta', w', l) dP(\theta', w' | \theta_t, w_t).$$

Labor demand at time t is then given by

$$l_t^*(\theta_t, w_t, l_{t-1}) = argmax_l \ \left(\theta_t f(l) - w_t l - C(l - l_{t-1}) + \beta \overline{V}(\theta_t, w_t, l) \right). \tag{7}$$

We divide firms into two groups: those that adjust their labor, and those that do not.

2.1.1 Adjusting Firms

Lemma 1 summarizes the first-order conditions that hold for adjusting firms.

Lemma 1. *Assume $V(\cdot)$ is differentiable in l. When $l_t^* > l_{t-1}^*$, l_t^* satisfies*

$$\theta_t f'(l_t^*) - w_t + \beta \frac{\partial \overline{V}(\theta_t, w_t, l_t^*)}{\partial l} = 0. \tag{8}$$

When $l_t^* < l_{t-1}^*$, l_t^* satisfies:

$$\theta_t f'(l_t^*) - (w_t - c) + \beta \frac{\partial \overline{V}(\theta_t, w_t, l_t^*)}{\partial l} = 0. \tag{9}$$

Proof
The result follows directly from optimization when an interior solution exists.#
In the special case when $c = 0$, the continuation value is unaffected by the choice of labor in the current period, so both (8) and (9) reduce to the "myopic" per period maximization solution that we reported earlier in the case of no firing costs.

We use a perturbation approach to recover the change in the continuation value arising from a small change in labor. We amend the standard two-period Euler equation approach to accommodate the possibility of periods of non-adjustment by pushing the optimal program forward until the firm adjusts again, as in Pakes (1994). Let the variable τ take on positive integer values, and define the next adjustment time as $t + \tau^*$, so τ^* is given as

$$\tau^* = min_{\tau \geq 1} \{ l^*(\theta_{t+\tau}, w_{t+\tau}, l_t) \neq l_t \}. \tag{10}$$

τ^* is a random variable from the firm's perspective because it does not know with certainty the next period in which it will adjust.

Corollary 1 is the first-order condition.

Corollary 1. *When $l_t^* > l_{t-1}^*$, l_t^* satisfies*

$$\begin{aligned} \theta_t f'(l_t^*) &- w_t \\ &+ E_t[\textstyle\sum_{\tau=1}^{\tau^*-1} \beta^\tau(\theta_{t+\tau} f'(l_t^*) - w_{t+\tau})] \\ &- E_t[\beta^{\tau^*} 1\{l_{t+\tau^*}^* < l_t^*\}\, c] = 0, \end{aligned} \tag{11}$$

When $l_t^* < l_{t-1}^*$, l_t^* satisfies:

$$\begin{aligned} \theta_t f'(l_t^*) &- (w_t - c) \\ &+ E_t[\textstyle\sum_{\tau=1}^{\tau^*-1} \beta^\tau(\theta_{t+\tau} f'(l_t^*) - w_{t+\tau})] \\ &- E_t[\beta^{\tau^*} 1\{l_{t+\tau^*}^* < l_t^*\}\, c] = 0, \end{aligned} \tag{12}$$

See Appendix for proof.

l_t^* is the solution to (11) or (12). It equates expected marginal revenue with expected marginal costs, accounting for possible periods of non-adjustment. Comparing (11) and (12) to (8) and (9), it is apparent that $\beta \frac{\partial \overline{V}(\theta_t, w_t, l_t^*)}{\partial l}$ is equal to the additional terms given by the expectations. Hiring costs would add an additional term to each expression, further complicating the solution.

The main results are as follows. With non-convex adjustment costs, there could be multiple levels of l that satisfy this equality, and proving uniqueness without stronger assumptions is difficult (see e.g. Caballero and Engel (1999)).[9] If we assume it is a function, it is an implicit one, and may be non-linear in its arguments, requiring non-parametric techniques which can weaken the power of any test using estimated labor demand. Also, as application of the implicit function theorem to (11) and (12) shows, the probability of adjusting is not necessarily monotonically falling as firing costs increase. Similarly, and hiring and firing conditional on adjusting are also not necessarily attenuated toward zero as firing costs increase.

Corollary 1 may be easier to interpret if we write down the first-order condition for a firm that knows the next period of adjustment τ^* and is hiring labor in period t. Let $F_{t+k}(\theta_t, w_t, l_t, C) = E_t[1\{l_{t+k}^* < l_t^*\}]$ denote the probability of the event that a firm fires k periods from time t, given what is known at t. We denote this probability as F_{t+k} throughout. Conditional on knowing the next period of adjustment τ^* we write $F_{t+k|\tau^*}$, and note that for $k < \tau^*$ the probability of firing (and hiring) is equal to zero. Labor demand l_t^* then satisfies

$$\begin{aligned} \theta_t f'(l_t^*) &- w_t \\ &+ E_{t|\tau^*}[\textstyle\sum_{\tau=1}^{\tau^*-1} \beta^\tau(\theta_{t+\tau} f'(l_t^*) - w_{t+\tau})] \\ &- \beta^{\tau^*} F_{t+\tau^*|\tau^*} c = 0. \end{aligned} \tag{13}$$

[9] They are only able to prove that their investment policy function does not have an infinite number of solutions.

For example, when $\tau^* = 2$, (13) implies $l = l_t^*$ satisfies

$$\begin{aligned} \theta_t f'(l_t^*) \quad & - \quad w_t \\ & + \quad E_{(t|\tau^*=2)}[\beta(\theta_{t+1} f'(l_t^*) - w_{t+1})] \\ & - \quad \beta^2 F_{(t+2|\tau^*=2)} c = 0. \end{aligned} \tag{14}$$

The firm accounts for the one period of inactivity by adding to the first-order condition expected discounted marginal revenue less expected discounted marginal costs for that inactive period, evaluated at θ_{t+1}, w_{t+1}, and l_t^*. The additional liability of the new worker is accounted for by the expected discounted firing costs times the expected probability of firing. (11) and (12) generalize to the case of τ^* unknown.

For the simplest case of dynamics, Corollary 2 illustrates when increases in firing costs attenuate hiring and firing toward zero. Specifically, we consider a firm that adjusts this period and believes with probability 1 that it will adjust again in the next period. Let F_l be the derivative of the probability of firing workers in the next period with respect to an increase in the number of workers in the current period, and F_c be the derivative of the probability of firing workers in the next period with respect to an increase in firing costs this period. Define $\varepsilon_{Fc} = \frac{F_c c}{F_{t+1}}$ as the elasticity of the probability of firing tomorrow given an increase in firing costs today. The expectation of the probability of firing tomorrow - F_{t+1} - is taken with respect to $\tau^* = 1$ throughout, although we do not explicitly write the conditioning argument.

Corollary 2. *Assume a firm adjusting this period believes with probability 1 that it will also adjust next period. If $F_l > 0$, then hiring becomes increasingly attenuated as c increases if $\varepsilon_{Fc} > -1$, and firing becomes increasingly attenuated as c increases if $\varepsilon_{Fc} < \frac{1}{\beta F_{t+1}} - 1$.*

See Appendix for proof. In this case the change in the continuation value from Lemma 1 is given by the change in the expected firing costs $-\beta F_{t+1} c$.

For hiring firms the requirement for monotonically declining hiring is that the probability of firing next period not fall too much in response to the increase in firing costs. When $F_c < 0$, if

$$\varepsilon_{Fc} < -1,$$

$\beta F_{t+1} c$ decreases toward zero as c increases, which works to increase the number of hires, as (8) shows. The fall in the probability of firing is high enough such that the negative effect of the increase in the firing cost (to be paid in the future) is offset by the fall in the future probability that this worker is fired.[10]

[10]With $F_c \geq 0$ the monotonicity follows trivially.

For firing firms, the requirement for monotonic attenuation of number fired in c is

$$\varepsilon_{Fc} < \frac{1}{\beta F_{t+1}} - 1.$$

Since $\frac{1}{\beta F_{t+1}} - 1 > 0$, $F_c < 0$ yields monotonicity.

More general cases are more difficult to characterize because of the additional terms in Corollary 1 associated with the periods of non-adjustment. Similarly, all of the analysis for this simple case has assumed $F_l > 0$. If the probability of firing is decreasing the number of laborers that are employed, then these results must be revisited, as the number of possible outcomes increases significantly.

2.1.2 Non-adjusting Firms

For firms that do not adjust their labor, optimization tells us that, given their current level of labor l_{t-1} and productivity outcome θ_t, the firing costs exceed the change in profits that the firm would obtain at any alternative attainable level of labor:

$$\begin{aligned} C(l - l_{t-1}; c) & \geq \theta_t f(l) - wl + \beta \overline{V}(\theta_t, l; c) \\ & -(\theta_t f(l_{t-1}) - wl_{t-1} + \beta \overline{V}(\theta_t, l_{t-1}; c)) \quad \forall l. \end{aligned} \tag{15}$$

We derive the implications, simplifying the analysis slightly to ease exposition by assuming wages are permanently fixed at w and there are no fixed costs of adjustment.

Given l_{t-1} and firing costs $C(\cdot; c)$, define Θ_c be the set of θ such that the firm does not adjust labor:

$$\begin{aligned} \Theta_c = & \{\theta : (\theta f(l) - wl) - (\theta f(l_{t-1}) - wl_{t-1}) \leq \\ & C(l - l_{t-1}; c) + \beta(\overline{V}(\theta, l_{t-1}; c) - \overline{V}(\theta, l; c)) \quad \forall l\}. \end{aligned} \tag{16}$$

We suppress this set's dependence on l_{t-1}. The implications of (16) for how the probability of adjustment changes as firing costs increase are not obvious. Lemma 2 provides a set of sufficient conditions such that the probability of not adjusting is weakly increasing in firing costs. The result relies on how, as firing costs increase, the difference in continuation values changes for firms with the same θ but different levels of labor.

Lemma 2. *Given l_{t-1}, if*

$$\frac{\partial^2 \overline{V}(\theta, l; c)}{\partial l \partial c} \leq 0, \tag{17}$$

and

$$|l - l_{t-1}| \geq \beta \left| \frac{\partial(\overline{V}(\theta, l_{t-1}; c) - \overline{V}(\theta, l; c))}{\partial c} \right| \quad \forall l < l_{t-1}, \tag{18}$$

then the probability that a firm does not adjust its labor is weakly increasing in firing costs c.

See Appendix for proof. If the condition is to hold in the aggregate, it must hold for all possible initial labor levels l_{t-1}.

We interpret the conditions. The first assumption is related to the fact that

$$\frac{\partial \overline{V}(\theta, l; c)}{\partial c} \leq 0,$$

as for any (θ, l) the value of being in operation decreases as firing costs increase. (17) requires firms with the same productivity shock but more labor to experience *greater* decreases in value as firing costs increase. Intuitively, if one firm has more labor than another, then the firm with more labor has its total potential liability in firing costs increase more than the firm with fewer laborers. This assumption ensures that firms with a given (θ, l_{t-1}) that do not find it profitable to hire when facing c continue to not find it profitable to hire for $c' > c$.

The second assumption ensures that firms that do not want to fire given their current (θ, l_{t-1}) and c continue to not want to fire for $c' > c$. For a firm that currently has l_{t-1} employees and wants to fire $|l - l_{t-1}|$ employees, the marginal increase in firing costs for a small increase in c is $|l - l_{t-1}|$. This assumption requires the marginal increase in firing costs $\forall l < l_{t-1}$ be greater than the expected increase in future discounted values between a firm with l_{t-1} and l employees that occurs in response to this increase in firing costs.

2.2 Undoing the Distortion with Contracts

If there is efficient bargaining between the worker and the employer a contract can be written specifying a side payment from the worker to the firm that fully offsets the firing cost (Lazear (1990)). Consider one such scheme for the 2-period case with no discounting and a constant wage.[11] The firm pays w in period 1 to the worker, with the worker agreeing to set aside c until period 2. In period 2, if $\theta_2 < \theta_1$, each worker who is fired receives c. All retained workers receive $w + c$. If $\theta_2 \geq \theta_1$, then retained workers receive $w + c$ and new hires get w.

This contract allows the firm to pay firing costs out of the worker's salary from the previous period. The optimal choices of labor and the hiring and firing rule remain unchanged from the non-distorted setting. The marginal cost faced by the firm is w in each period regardless of whether the firm hires or fires. Workers' labor force participation choice is also unaffected, as they receive the same wage as in the regime

[11] This contract can be written for the infinite-horizon case, with the firm and the worker agreeing to a similar arrangement period-by-period.

with zero firing costs. Since no distortions are introduced into the market, efficiency means welfare continues to be maximized.

Lazear (1990) argues that the inefficiency may be difficult to undo using side payments for many practical reasons. In particular, workers must be willing to make the side payments to the employer or into an insurance fund; apprehension on the part of workers regarding the future severance payment could prevent the distortion's undoing.[12] Also, from an efficiency standpoint, firing probabilities are dependent on worker characteristics and firm layoff experience, so any unemployment insurance plan that does not condition on these factors is not going to maximize welfare.

2.3 Imperfect Competition and Strategic Interactions

With imperfect competition or when firms' strategically interact with one another, current choice variables are a function of all relevant state variables. We consider the case without firing costs first, so labor is not a state variable, and we suppress the time index. As in Section 2.1, firms differ in their productivity level, which is either an efficiency difference, a demand difference, or both. We assume J single-product firms compete against one another in a differentiated product setting.[13] Labor demand for firm k solves

$$P_k(1+\epsilon_{P_kQ_k}) * \frac{\partial Q_k}{\partial l} = w,$$

where P_k and Q_k are price and quantity sold of k, and $\epsilon_{P_kQ_k}$ is the elasticity of the price of k with respect to quantity sold. Nash behavior requires that labor choices are best responses. When goods are substitutes, the price and quantity demanded of good j will be a function of the entire vector of plant-level productivities (and the wage), so the functions $P_k(\cdot)$ and $\epsilon_{P_kQ_k}(\cdot)$ are written with arguments $P_k(\theta^1,\ldots,\theta^J,w)$ and $\epsilon_{P_kQ_k}(\theta^1,\ldots,\theta^J,w)$. Labor demand is thus also a function of the same arguments:

$$l^{*k} = l^k(\theta^1,\ldots,\theta^J,w).$$

Estimation of labor demand using (θ^1, w) as the two regressors in a market with competitors is misspecified, as there are multiple values of l^{*1} associated with (θ^1, w).

With firing costs or more complicated forms of strategic interactions, labor demand for firm k is determined by the wage, firm k's productivity, all competing firms' productivities, and similarly own- and competitor- stocks of labor:

$$l_t^{*k} = l_t^k(l_{t-1}^1,\ldots,l_{t-1}^J,\theta_t^1,\ldots,\theta_t^J,w_t). \tag{19}$$

[12] Even if the workers are willing to make side payments, other problems exist, including potential moral hazard problems like workers attempting to obtain the severance package early, or agency problems like managers colluding with workers to extract excess severance payouts in the face of full insurance.

[13] With multi-product firms, the analysis is more complicated, but the result is similar.

Again, estimation of labor demand using only $(l_{t-1}^k, \theta_t^k, w_t)$ as regressors is misspecified, as

$$l_t^{*k} = l_t^k(l_{t-1}^k, \theta_t^k, w_t)$$

is a correspondence.

3 The Gap Methodology

In models where job security policies are not undone through contracting, Section 2 tells us that firing costs drive a wedge between the marginal revenue product and the marginal input price (the wage). From a social planners' perspective, firms should choose labor to equate the wage w_{it} with the marginal revenue product (MRP), given by

$$MRP_{it} = P_{it} * \frac{\partial Q_{it}}{\partial l},$$

where $\frac{\partial Q_{it}}{\partial l}$ gives the increase in output associated with a small increase in labor. We define the gap, G_{it}, as the difference:

$$G_{it} = MRP_{it} - w_{it}.$$

In a setting with price-taking firms and no distortions, G_{it} is zero. With firing cost distortions, imperfect competition, or strategic interactions, equations (11), (12), and (19), illustrate the extra terms entering G_{it}. We start by focusing on the absolute values of the gaps, concluding as a social planner might that an increase in the average gap is suggestive of a negative impact on economic efficiency.

In order to estimate the marginal product of labor at the firm level, we posit a Cobb-Douglas production function:

$$q_{it} = \beta_s l_{it}^s + \beta_u l_{it}^u + \beta_k k_{it} + \beta_m m_{it} + \beta_e e_{it} + \beta_S S_{it} + \varepsilon_{it}$$

where q_{it} is the log of the real output, m_{it} is log of real value of intermediate materials, l_{it}^s is the log of the number of skilled (white collar) employees, l_{it}^u is the log of the number of unskilled (blue collar) employees, k_{it} is the log of the real capital stock employed, and S_{it} is log of the services used by firm i in year t.

The error, ε_{it}, is assumed equal to

$$\varepsilon_{it} = \omega_{it} + \eta_{it},$$

with ω_{it} the transmitted component of the firm specific productivity shock, and η_{it} the firm specific iid shock. We assume ω follows a first order Markov process (as in

Olley and Pakes, 1996). The latter error is assumed to have no impact on the firm's decisions, while the former can be correlated with input choices.

Given the production function specification and observed input levels, the marginal product is straightforward to calculate once one determines what "error" should be conditioned upon. For example, if both ω_{it} and η_{it} are productivity, then ε_{it} should be conditioned on in the calculation. With the Cobb-Douglas production function, for skilled labor, firm i operating in year t has a marginal product ($\frac{\partial Q_{it}}{\partial l}$) given by:

$$\frac{\partial Q_{it}^s}{\partial l} = \beta_s e^{\varepsilon_{it}} (l_{it}^s)^{\beta_s - 1} (l_{it}^u)^{\beta_u} (k_{it})^{\beta_k} (m_{it})^{\beta_m} (S_{it})^{\beta_S} (e_{it})^{\beta_e} = \beta_s * \frac{Q_{it}}{l_{it}^s}.$$

If η_{it} is measurement error, then we will only want to condition upon ω_{it} when the marginal revenue product is calculated. In this case, given the first-order Markov assumption on ω_{it}, we predict ω_{it} given ω_{it-1} by projecting $\hat{\varepsilon}_{it}$ on a polynomial in $\hat{\varepsilon}_{it-1}$ and then calculating the marginal revenue product at this predicted value. We experiment with these different approaches when we get to the data.

We look at the absolute value of the gap between marginal revenue product and marginal input price for skilled and unskilled labor, G_{it}^s and G_{it}^u, and for materials G_{it}^m and electricity G_{it}^e:

$$G_{it}^s = |MRP_{it}^s - w_{it}^s|$$
$$G_{it}^u = |MRP_{it}^u - w_{it}^u|$$
$$G_{it}^m = |MRP_{it}^m - P_{it}^m|$$
$$G_{it}^e = |MRP_{it}^e - P_{it}^e|,$$

where P_{it}^m is the price for materials and P_{it}^e is the price for electricity. These gaps are linear in the marginal revenue product and the wage. In terms of rates of convergence, $\sqrt{n}$ consistency of the gap follows directly from $\sqrt{n}$ consistency of estimators for each of these components, which is often trivial to establish for commonly used production function estimators. This contrasts with the slower convergence rates for estimators of labor demand when it is regarded as a non-linear function of its arguments and non-parametric estimators must be used.

In many cases, an aggregate output price deflator is used to translate observed firm revenues $P_{it}Q_{it}$ into units of quantity. We denote this aggregate price index $\overline{P}_t$. When $P_{it} \neq \overline{P}_t$, a new term enters into the residual:

$$\varepsilon_{it} = \omega_{it} + \eta_{it} + lnP_{it} - ln\overline{P}_t.$$

If this new source of error $(lnP_{it} - ln\overline{P}_t)$ is uncorrelated with input choices, then no further estimation questions related to the production function are raised beyond simultaneity of inputs and ω.[14]

When calculating the marginal revenue product we will want to include plant-level price differences. If we include the full residual $\hat{\varepsilon}_{it}$, then we are calculating the marginal revenue product using the entire difference between the firm price and the aggregate price index, and assuming that η_{it} is all productivity. If we regress $\hat{\varepsilon}_{it}$ on $\hat{\varepsilon}_{it-1}$, we get a forecast of the expected value of ω_{it} *plus* the expected difference between firm price and the aggregate price index.

3.1 Markups and the Marginal Revenue Function

The analysis does change if we forsake recovery of the production function parameters and instead resolve ourselves to estimation of the parameters of the marginal revenue function. From this perspective, the marginal effects of varying input levels on revenue are recovered from regressing the log of deflated total revenue on log-levels of inputs.[15] Setting aside estimation issues, the recovered coefficients from the revenue production function reflect both the marginal product and the markup. This means estimated gaps will reflect both $P_i * \frac{\partial Q_i}{\partial l}$ and a markup term. For example, with a single-product firm, using estimates of the revenue production function produces an estimated gap:

$$G_{it} = P_{it}(1 + \epsilon_{P_{it}Q_{it}}) * \frac{\partial Q_{it}}{\partial l} - w_{it},$$

where $\epsilon_{P_{it}Q_{it}}$ is the elasticity of price with respect to quantity. The new term reflects lost revenue on infra-marginal demand due to the fall in price caused by increasing labor, which increases quantity.

If information on demand elasticities are available, they can be combined with the plant-level information to hold this part of the gap constant. The analysis can proceed as before, looking at the absolute value of the gaps.

When demand elasticities are not available, we must restrict ourselves to looking at changes in gaps for plants that have positive gaps, as Figure 3 illustrates. Firms with positive gaps are firms for which marginal revenue exceeds the wage. Their output is less than monopoly output, denoted $Q_{Monopolist}$. From the point of view of the social planner, if these gaps become larger, welfare falls, as when we move from D to E in Figure 3.

[14] Additionally, we could use the alternative proposed in Griliches and Klette (1996) and used in De Loecker (2005), deriving this term based on assumptions made on the demand system.

[15] The aggregate price deflator is still used to control for inflation.

For firms where both gaps are not positive, the existence of the markup term makes analysis of the change in the absolute value of the gap ambiguous. For example, consider a negative gap that becomes more negative in response to firing costs. If this reflects a move from A to B, then the absolute value of the gap increases but economic efficiency improves because the price-wage gap falls. It is also possible to find cases where the measured gap becomes more negative and economic efficiency decreases, as with a move from A to C. Similar examples of this type of ambiguity can be told for firms that have positive gaps that become negative, and for firms that have negative gaps that become positive.

4 The Chilean Job Security Reforms

Workers in Chile have traditionally been provided with job security through three means: advance notices for dismissal, limitations on the use of fixed-term labor contracts, and severance payments on dismissal.[16] Over the 1979-1996 sample period, advance notice was unchanged at one month, and we know of no evidence of significant changes in the use of fixed-term contracts. Severance payments did change substantially on two occasions, particularly for workers that were fired for "economic" reasons. We look at these changes for evidence of an impact on economic efficiency.

There are two types of fired workers in Chile, those fired "justly" and those fired "unjustly." "Just cause" was defined in the Immobility Law of 1966, and it stated that criminal behavior and absenteeism (for example) qualified as reasons to fire someone without paying severance. Under this law economic and financial needs were technically "just."

In 1978, the Pinochet administration started requiring firms to pay one month's wages per year of service, subject to no upper limit, for any worker dismissed for "unjustified reasons." The *Labor Plan* of 1980 formalized this arrangement, mandating that severance packages be part of the overall job contract negotiated between the employee and the employer. It applied to all labor contracts signed after August 1981, and it restricted the minimum severance package for "unjustified reasons" to one month's wages per year of service, subject to a maximum of five months.

We first look at the impact of the enhancement in job security that occurred in June 1984, when economic and financial needs were reclassified to "unjustified." Then, in December 1990, the new democratic regime strengthened the provision. While technically reclassifying firings for economic and financial difficulties as "just,"

[16]This section draws heavily from the comprehensive treatment given in Edwards and Edwards (2000).

the severance package for unjust firings became the package for "just" firings, and it was further strengthened by raising the maximum severance package from five to eleven months' wages, one month per year employed. The law also placed the burden of proof of economic cause on the employer, charging the employer a further 20% penalty when the case could not be established to the satisfaction of the court.

Pagés and Montenegro (1999) construct an index that reflects the expected present value of the firing costs associated with hiring a given laborer. Let β denote the discount factor, δ the probability of retention, b the cost of advance notice, a_t the probability that economic difficulties of the firm are considered "just," S^J_{t+s} the payment under justified cause, and S^U_{t+s} the payment under unjustified dismissal. $\delta^{(s-1)} * (1-\delta)$ is then the probability of firing after s years.[17] The index is given as

$$C_t = \sum_{s=1}^{T} \beta^s \delta^{(s-1)} * (1-\delta) * \left(b + a_t S^J_{t+s} + (1-a_t) S^U_{t+s}\right).$$

Figure 2 is calculated using their best estimates for a firm in Chile, with β equal to 0.92, δ equal to 0.88, b equal to 1, a_t starting at 0.8, falling to 0 from 1985-1990, and then increasing in 1991 to 0.9, S^J_{t+s} zero until 1990 when it increases to one month's pay for every year worked up to 11 months maximum, and S^U_{t+s} at one month's pay for every year worked up to 5 month's maximum, for 1981-1990, and then increasing to 1.2 month's pay for every year worked up to a maximum of 11 months.

Figure 2 shows that firing costs in the pre-1984 period were low, close to 0.75 months of wages, and were primarily determined by the cost of advance notice. Job security was then significantly enhanced by the reform in mid-1984, and then again by the reforms of late 1990. By the end of the sample period the average expected cost of firing at hiring had increased to more than three months wages in Chile. To put this into context for 41 OECD and Latin American countries together, Chile went from having one of the smallest levels of firing costs to being above the median of 2 months wages, although remaining well below the 10-14 month range of Colombia, Brazil, Peru, and Ecuador (see Figure 1).

There are a number of other political and economic changes taking place over the sample period, many of which have been analyzed elsewhere. The Labor Plan reduced payroll taxes substantially in 1981. Gruber (1997) reports that these reductions were fully passed on to wages with no effect on unemployment. The bargaining power of unions was relatively low through the 1980s under the military government, but increased under reforms introduced by the democratic regime in 1991. Using aggregate

[17] A more comprehensive approach would have indices for both the firm and the worker, C_{ijt}, although this calculation would require matched employer-employee data.

data and time series analysis, Edwards and Edwards (2000) find that reduction of payroll taxes and decentralization of bargaining increased labor market flexibility and contributed to a reduction in employment. Finally, there was a severe recession in 1982 related to the Latin American debt crisis and the fall in copper prices, a major Chilean export. The recovery was also quite remarkable, with wages increasing at 5% a year and unemployment falling from 17% to 5.5% in the post-recession period.

Our empirical approach uses the 1979-1984 as the control period, and compares the two treatment periods, 1985 to 1990 and post-1990, to look for evidence of an impact on efficiency. We condition on as many potential confounding factors that we observe, like unemployment, plant-level and aggregate output, and plant-level wages and productivity. We also look closely at the times when the reforms were put in place - before and after - in order to try to control for other unobserved confounding factors.

5 The Data

We use the annual Chilean Manufacturing Census (Encuesta Nacional Industrial Anual) conducted by the Chilean government statistical office (Instituto Nacional de Estadistica). The survey covers all manufacturing plants in Chile with more than 10 employees and has been conducted annually since 1979. Our data covers the seventeen year period from 1979 to 1996. There are about 5000 firms every year, with an entry rate and exit rate of about 5 percent over the panel period.

This survey has been used in a number of previous studies.[18] The survey provides an industry indicator, and measures of output, inputs, wages, employment and investment. A detailed description of how the longitudinal samples were combined into a panel from 1979-1986 can be found in Liu (1991). We extended this to 1996 following broadly the procedure used by Liu. Further, we supplemented the raw data with additional information on price series for output, machinery and inputs from other sources including IMF's IFS database, data on price indices obtained from the Chilean government statistical office, and also with data from Edwards and Edwards (2000) and Edwards and Edwards (1991).[19]

Plant-level real output is total revenue deflated with a 4-digit industry output deflator obtained from the Web site of the Chilean Government's statistical office. Industry real output is the sum of these plant-level real outputs by 4 digit (ISIC)

[18] See Levinsohn and Petrin (2003), Pavcnik (2000), Roberts and Tybout (1996), Hsieh and Parker (2006)), for example.

[19] We thank Andrés Hernando for providing us with some of these deflators.

industry. Real materials and services are both aggregates at the plant-level, and each have their own 3-digit price deflator.[20] Electricity usage is separately reported from other energies, and it has its own deflator.

At each firm we observe the total wage bill and total person-years for several types of laborers, and we perform the standard aggregation into blue collar and white collar workers. The components of the wages are given as Wages, Bonus, Payroll Taxes, and Family Allowance Taxes. While there is not an explicit category for firing costs, our understanding is these costs appear in the wage bill when they are incurred by the firm.[21] We divide total wage bill by number of workers to get average wage. The real wage rate is obtained by deflating the wage rate using the output deflator.

The real capital series is constructed using the perpetual inventory method. Data on book value of capital is available for the years 1980-81 and 1992-96. We use the same methodology as Liu (1991) to construct the capital series for all firms for which we have data on book value for 1980-1991. For other firms, we build capital series backward and forward using the data on book value available for 1992-96. As in Liu, we assume a 5% depreciation rate for buildings, a 10% depreciation rate for machinery, and a 20% depreciation rate for vehicles. We use a deflator for the construction sector to deflate investments in buildings and use a deflator for machinery to deflate investments in both machinery and vehicles. The capital series we use is constructed using the 1980 base year, where firms with missing values for this year are replaced using the capital series constructed using 1981, 1992, 1993, 1994, 1995 and 1996 in that order.

We examine general trends in the average real wage rates in Figure A1 and unemployment and inflation rates in Figure A2. Using the plant-level data, we find that both blue and white collar real wages dropped till about the mid 1980s and then grew through the late 1980s and early 1990s, starting after unemployment levels out around 5% in 1987. The spike in unemployment rates in the early 1980s seem to be driven by the deep recession around the same period. The overall trend in the real wage rate seems to be strongly influenced by macroeconomic trends.

6 Estimation

Our goal is to estimate the marginal revenue product and the marginal input price. For the marginal revenue product, we estimate the gross output production function

[20] Over 30,000 plant-year observations report zero fuel use, so we deflate fuels with its own aggregator and combine them with materials. Results are robust to dropping these observations. Services purchased include freight, insurance, rent, accounting, communications, advertising, and technical support.

[21] Dr. Alejandra Cox-Edwards advised us on this point. Our results are robust to using only Wages and Bonus.

separately by 3-digit ISIC code for the 27 industries that have more than 100 observations over the entire sample period. We use the Levinsohn-Petrin (2003) estimator (LP), which is easy to calculate and addresses the simultaneity problem raised in Marschak and Andrews (1944).[22] We also report estimates from a plant-level fixed effects specification, which allows for a potential simultaneity problem but imposes $\omega_{it} = \omega_i$ for all t. We focus on the LP approach because it allows ω_{it} to vary over time and be correlated with input choices, although our findings are robust across these and other estimators.[23]

The second component of the gap is the marginal cost for the input. Our data is annual, so for labor this is the wage that must be paid for an additional year of labor. At each plant we observe total annual wage bill, which we divide by the number of laborers to get an average plant-level wage. Our approach requires this average wage to be a good proxy for the marginal wage. We discuss several estimation issues that may arise.

As mentioned earlier, our understanding is that plants add firing costs to reported wages when they are incurred. For plants that fire workers, this causes the estimated average wage to be higher than the marginal wage, and this difference is likely to systematically change in response to increases in firing costs, potentially confounding our gap analysis.

We estimate the size of this error using an observed probability of firing of 39.2% (from Table 6), an observed average fraction of workers fired given a firing spell of 17.9% (from Table 7), and an average tenure of 5 years for workers, which leads to maximum payment for the first increase in firing costs. The product of these terms suggests that the estimated average wage overestimates the marginal wage by 2.8%. This quantity is small when compared to the size of our estimated gaps. More importantly, though, is that approximately 70% of the estimated gaps for both blue and white collar labor are positive.[24] For these plants, the error *reduces* the magnitude of the estimated gap relative to its true size.

Increases in firing costs may lead to a more intensive use of overtime relative to the hiring of new workers. If there are no overtime premia, there is no bias. If overtime premia are being paid and the marginal worker would be hired with overtime, then the average wage equals the marginal wage. For example, if firing costs lead a firm

[22] Stata code is available for this setup, the gross output production function setup, and other formulations of the Levinsohn-Petrin estimator. See Petrin, Levinsohn, and Poi (2004).

[23] Other proxy methods are Olley and Pakes (1996) and the modified-LP estimator suggested by Ackerberg, Caves, and Fraser (2006), which uses the same invertibility condition as LP but only a subset of the moments proposed by LP for estimation.

[24] This fraction is almost the same for firms that are hiring, firing, or doing neither. It is also similar across blue and white collar workers, as 98% of firms with a positive blue collar gap have a positive white collar gap.

to hire two workers with overtime instead of three workers without overtime, then as long as all current workers are being paid overtime, there is no measurement problem. If the marginal worker would not be hired with overtime, then the average wage is higher than the marginal wage. Similar to the firing cost case, for the 70% of plants that have positive gaps, overtime premia lead to underestimates of the gaps.

In our data there is variation in the wage rates across plants for both blue and white collar labor. If these differences exist because of market imperfections, then these wages are the marginal wages and there is no measurement problem. If they reflect differences in labor quality, then labor quality is measured with error. The estimated average wage remains correct, but the marginal revenue product will be estimated with error for two reasons. First, the measurement error affects the consistency of the production function estimates. Second, since the marginal revenue product is declining in inputs, we will over- (under-) estimate the marginal revenue product for plants with labor that is of higher (lower) quality than that measured.

We do not allow the production function estimates to vary by firing cost regime. Presumably the amount of measurement error in labor quality does not change in response to increases in firing costs. For these reasons we do not believe this error in the marginal revenue product would vary in a way that would lead to finding larger gaps in periods of higher firing costs. Indeed, if the error is akin to classical measurement error, it works in the opposite way, weakening the power of the gap as a test statistic. We now turn to the results.

7 The Gap Results for Chile, 1979-1996

Over the entire sample period we observe 54,230 gaps for blue collar, with 15,599 observations from 1979-1984, 17,834 observations from 1985-1990, and 20,797 observations from 1991-1996.[25] Before conditioning on plant-specific differences and other observed control variables, we analyze the unconditional means and medians of the gap distribution. We work in levels - thousands of 1979 Chilean pesos - so changes in the gap are comparable to the observed annual wage.[26] In our data blue collar workers are paid on average 83 thousand pesos a year and white collar workers are paid 160 thousand pesos a year. The average (median) unconditional gaps for blue

[25] For four of the smaller twenty seven industries, there is not sufficient variation to identify the capital coefficient using the LP estimator. The fixed effects estimator protects against fewer endogeneity problems but dispenses with less variation, adding back these 6,500 plant-year observations (see Table A1). Results are very similar across the two estimators.

[26] As we note later, the robustness results include log specifications, and the results are similar to what we report for the levels specifications. When working in levels, we replace the biggest 2% of the gaps with the value of the 98%ile, and similarly for the smallest 2% of the gaps (we "Winsorize" the observations).

collar labor across the three periods are 105 (36), 146 (45), and 182 (41) thousand pesos. The average (median) unconditional gaps for white collar labor across periods are 173 (90), 213 (101), and 253 (106). While the magnitudes change when we condition on additional covariates, this pattern of increases is remarkably robust.

We also analyze changes in the dispersion of plant-level gaps. We design our dispersion measure to maintain the same units as the gap measure. We predict expected plant-year gaps by regressing observed plant-level gaps on plant fixed effects and two indicator variables that allow changes in firing costs to affect the prediction, one for 1985-1990 and one for 1991-1996. We then deduct the prediction from the observed plant-level gap, and take the absolute value. We find that the average (median) dispersion for the blue collar labor starts at 101 (73), then increases to 125 (90) for 1985-1990, and increases again to 145 (106) for 1991-1996. For white collar the average (median) dispersion across periods increases from 140 (118) to 157 (124), and then to 174 (131). Overall, both the first and second moments of the unconditional gap distribution increase as firing costs increase.

In Table 1 we report the regression analysis for blue collar labor, white collar labor, materials, and electricity. In each column the absolute value of the gap for the input is the dependent variable. All regressions include two period-indicators for the different degrees of job security, one for 1985-1990, and one for 1991-1996. Columns 2, 4, 6, and 8 also include the industry output growth rate as a control. The fixed effects allow for base-period plant-specific gaps, so the magnitudes of the period dummies are identified by within-plant variation in the mean gap over time.

The regressions suggest that the base-period average gap for blue collar labor was 99 thousand pesos per year, and for white collar workers it was 175 thousand pesos per year. In the first period of treatment - with a maximum of five months severance pay - the blue collar gap increases significantly by 20 thousand pesos, while the white collar gap increases by 9 thousand pesos, although insignificantly. In the second period - with a maximum eleven months firing costs - the blue collar gap significantly increases another 13 thousand pesos. This second change in job security also increases the white gap by 15 thousand pesos relative to the first period, and this white collar change is statistically significant. The estimates are robust to controlling for changes in industry output, and to the other regressors described in the data section.

We also regress the dispersion measure on the period controls and plant fixed effects, and report these results in Table 2. Similar to above, the fixed effects allow for base-period plant-specific dispersion, and the time-period variables ask if this dispersion has on average increased in response to increases in firing costs. The results are starker than those associated with the absolute values of the gaps. For blue collar labor dispersion starts at 102 thousand pesos, then increases first to 122 thousand pesos and then to 145 thousand pesos. The white collar dispersion starts at 144 thousand pesos, increases to 157 thousand pesos, and then ends at 170 thousand pesos. All changes are statistically significant at 1%.

When markups exist, they enter as an additional term in the gap. Figure 3 shows that markups require us to restrict analysis to plants that have positive gaps in juxtaposed years; they are the only observations for which we know that economic efficiency decreases as the gap increases (and vice versa). Of the 54,230 observations from the base specification, 71% are positive, and almost all of these observations are juxtaposed next to positive gaps, leaving us with a sample size of 37,923 observations for blue collar labor. For this subsample, we rerun the regressions in Table 1.

While the base period gaps in Table 3 are slightly larger than those in Table 1 for both blue and white collar labor, the increases in the gaps are more pronounced. For blue collar labor the average gap increases from 113 to 143 thousand pesos, and then increases again to 159 thousand pesos in 1991-1996. For white collar the gap increases from 197 to 225 thousand pesos, and then climbs again in the second treatment period to 230 thousand pesos. When we use the plant-specific dispersion measure for these plants as the dependent variable (as in Table 2), the results are similarly striking.[27] Blue collar dispersion increases by 50 thousand pesos on a base period of dispersion of 114 thousand pesos, and white collar labor increases by 38 thousand pesos on a base period of 162 thousand pesos. All of the estimated coefficients for blue and white collar labor for both the gap and the dispersion are significant at 1%. One interpretation of these larger and more precise estimates is that the results in Tables 1 and 2 suffer from the noise that markups add, and this noise is most pronounced for white collar labor.

As control inputs we examine the gaps for materials and electricity, which are reported in Tables 1-3. Since these inputs are not directly affected by the job security provisions, we expect to find no concurrent increases in their gaps, similar in spirit to a difference-in-difference type estimator. For both materials and electricity, Tables 1-3 show that the average gaps and the dispersion in the gaps fall relative to 1979-1984. A difference-in-difference estimator would thus make the results from Tables 1-3 more pronounced.

We now look more closely at the year-to-year timing of the changes in gaps. Figure 4 plots the coefficients on the year dummy variables that come from regressions similar

[27] All unreported results are available from the authors on request.

to those reported in Tables 1-3, but that include the year-to-year dummy variables as opposed to just the two period controls. The 1980 coefficients are normalized to one in the figure.

The timing of the results are consistent with the timing of the job security changes. The labor gaps level off in post-recession 1982-83, are approximately flat until 1985, when they increase in 1986-87 after the first application of job security. The gaps appear to level off in 1988 at the higher levels. Then, with the next application of job security in 1990, both labor gaps start to gradually increase. The blue collar gaps continue to increase while the white collar gaps fall off slightly at the end of the sample period. Relative to 1984, the materials gap decreases slightly in the first period and then recovers to its 1984 level by 1996. Electricity falls slightly in the first treatment period relative to 1984, and then declines somewhat more substantially in the second treatment period. While both labor inputs appear to increase relative to 1984, the control input gaps are not increasing as firing costs increase.

Using the same regressions, Figure 5 and Figure 6 more closely examine the statistical significance of the year-to-year indicator variables relative to 1984 for both the absolute value of the gap and its dispersion for blue and white collar labor. In Figure 5 (6) two horizontal lines indicate the average level (dispersion) of the gap in 1984 for blue and white collar labor. Confidence intervals for yearly indicator variables that do not contain the line are significantly different from the 1984 level. All eleven of the blue collar year dummies after 1985 are significantly different from 1984 for both the average gap and for the average level of dispersion. Similarly, all eleven of the white collar dispersion indicators after 1985 are significantly different from 1984, and nine of the eleven average gaps for white collar labor are significantly different from 1984. If we conduct the analysis using the subsample that allows for markups, then all 44 of these indicators are statistically different from 1984. Overall, it appears not to matter whether we include the tumultuous years of the recession, as the specifications with the period indicators do, or whether we conduct the "discontinuity" analysis, with 1984 as the last period before the reforms. The results point to a significant increase in economic inefficiency that is introduced by firing costs.[28]

We performed the analysis in many different ways. Increases in economic inefficiency are apparent for trans-log production function specifications. They are apparent across quantile regression specifications evaluated at the 5th, 25th, 50th, 75th, and 95th quantiles, and to analysis of logs of absolute value instead of the

[28]The one difference is that the analysis with the annual indicators does not point to significant differences between 1990 and the 1991-1996 years.

levels. We estimated specifications that used the entire residual in the estimate of the marginal revenue product instead of just its predicted value and found similar results. We also explored whether we would find evidence of economic inefficiency if we used a value added specification, which imposes separability of intermediate inputs, but allows for a simpler specification to estimate. Results were also robust to value added specifications using either the Levinsohn-Petrin estimator or the fixed effects estimator. Overall, we believe the evidence is strongly in favor of the fact that these firing costs introduced economically and statistically significant costs to the economy.

8 Traditional Labor Demand Statistics

We look for an impact of job security increases using traditional approaches, all of which either directly estimate labor demand, or estimate some function of labor demand. We also look to see if wages change in a way that is consistent with offsetting the job security provisions. Our results appear inconclusive.

8.1 Labor Demand

We use the widely adopted log-linear regression specification (see, e.g. Blundell and Bond (1998)):[29]

$$l^u_{it} = \beta_0 + \beta_1 w^u_{i,t} + \beta_2 w^u_{i,t-1} + \beta_3 w^s_{i,t} + \beta_4 w^s_{i,t-1} + \beta_5 q_{i,t} + \beta_6 q_{i,t-1} + \beta_7 l^u_{i,t-1} + \epsilon_{it} \quad (20)$$

where i and t index firm and time, w^u is the log of unskilled (blue collar) wage rate, w^s is the log of skilled (white collar) wage rate, l^u is the log of unskilled (blue collar) employment and q is the log of value added.

We look at three statistics. Changes in the intercept and the slope coefficients suggest a change in demand, either through a change in the level or to the sensitivity in price (wage). Increases in the coefficient on lagged labor are also suggestive of a negative impact, as last period's labor becomes a better predictor of this period's level.

We estimate the dynamic labor demand equations using three approaches: OLS, instrumental variables, and fixed effects. The instrumental variable approach, which many may regard as the preferred specification, follows Blundell and Bond (1998). We consider as endogenous blue collar wage, white collar wage, value added and

[29] One motivation is given by considering a firm in a competitive environment with a Cobb-Douglas production function and an AR(1) disturbance. Similar dynamic labor demand equations have been estimated in a number of studies, including Hamermesh (1993), Sevestre and Trognon (1996), Fajnzylber and Maloney (2000), and the literature cited in Heckman and Pages (2004).

lagged blue collar employment. The instruments we use are lagged industry output, lagged industry average blue collar wage, lagged industry average white collar wage, two-period lagged industry output, two-period lagged industry average blue collar wage, two-period lagged industry average white collar wage, two-period lagged blue collar wage, two-period lagged white collar wage, two-period lagged materials, two-period lagged capital, two-period lagged value added and three-period lagged blue collar employment.

We recognize the potential problems with using lagged variables as instruments, but note that it is standard practice in the literature, in part no doubt because other instruments are not readily available. Indeed, weak instruments, or instruments which are correlated with the error, are two further reasons the labor demand equation may be problematic as a statistic of interest.

Table 4 presents the results for the instrumental variables specification, Table 5 has the fixed effects estimates, and the OLS specification is in Table A2 in the appendix. In estimating the demand functions for each of the three relevant periods, we use two alternative approaches. First, we allow only the intercepts and the lagged blue collar employment term to vary by period. Second, we allow all the coefficients to vary by period.

We start with the restricted IV specification reported in column 1 of Table 4. The period intercepts increase after the first treatment and then decrease after the second. The lagged labor coefficient also first increases towards 1, and then falls from 1. In the full specification, the intercept increases and then decreases. The coefficient on lagged labor monotonically increases toward 1, from 0.12 to 0.66. The price sensitivity parameter (on wage) first increases (in absolute) value, and then decreases. Overall, these results are hardly conclusive, although they may be suggestive.

For the fixed effects model, the constrained specification in the final column of Table 5 shows decreasing demand relative to the initial period, but an increasing and then non-changed coefficient on lagged labor. The unconstrained model has a decreasing and then increasing intercept, an increasing price sensitivity, and an increasing and then decreasing coefficient on lagged labor. OLS results are also mixed. There seem to be few common themes across the different estimators.

8.2 Probability of Adjustment

In Table 6, we examine whether firms less frequently change employment levels as firing costs increase (see Kugler (1999), for example). The dependent variable in our regressions equals one for firms that did *not* change net employment levels from the previous year.[30] Columns 1 and 2 indicate that the probability of not adjusting fell from 17% to 13% as firing costs increased. With fixed effects there is no change in probabilities as job security increases. If we use the production function estimates to condition on productivity residuals, we find a small *increase* in the probability of not adjusting using the LP residual, although not statistically significant. Using the fixed effects residual, the probability of not adjusting increases 1.2% in the first treatment and then to 3.6% in the second treatment, and is statistically significant.

8.3 Magnitudes Conditional on Adjusting

We look at whether fires conditional on firing decrease, and similarly, whether hires conditional on hiring decrease. The dependent variable is the year-to-year percentage change in the level of labor. Table 7 presents the results for the case of firing. Unconditionally, the magnitude of firing falls by 1.9% when firing costs first increase, and then falls again to 2.6% on the second dose (relative to the initial period). The results are similar with firm fixed effects. Once we condition on either productivity residual, the effects become more pronounced, as the average falls by 3.4% in the first period and then by 5.7% in the second period.

Table 8 present the hiring results. Unconditionally, in the first period hiring decreases by 1.2%, and the second period decreases further to 4.5%. With firm fixed effects, the numbers fall to 2.3% for the first period and 7.4% for the second period. However, conditional on either productivity residual, number of hires *increases*. For the fixed effects residual, hiring increases 2.3% in the first period and 2.6% in the second period. Across these increases in firing costs, hiring is not attenuated towards zero.

8.4 Wages

For an estimate of the per period reduction in wages required to offset the two job security changes introduced in Chile, we consider two "insurance" plans. Under the first, expected firing costs are recovered through premium payments over the lifetime of the worker in the firm. Under the second, the firm insures against the possibility of firing workers period by period.

In Appendix 1, we estimate the fair premium under these two insurance schemes for a change in job security equivalent to six months wages (comparable to the maximum increase in both of the Chilean changes). Our estimates suggest that a drop

[30] We only observe net hires, so we (like much of the literature) can only talk about change in net employment levels. See Hamermesh and Pfann(1996).

in wages in the range of 3% to 6% could provide the necessary offset.

To try to separate out the effect of job security changes on wages, we regress the estimated plant-level average real wage on period controls for the job security changes. The other controls include firm fixed effects, firm output growth rate, industry output and industry growth rate, and the unemployment rate. Unfortunately, we do not observe worker-specific covariates.

We report the estimates in Table 9. In all the specifications, there is a major decline in wages in period 2 (1985-1990). The extent of the decline, between 36% and 53%, is much larger than that required under our offset plans. In period 3 wages recover somewhat. Overall, there is no clear evidence that the job security changes were offset through lower wage rates.

9 Conclusions and Extensions

Firing costs are commonplace across the world. We agree with the sentiment from Heckman and Pages (2004) and Hamermesh (2004) that these provisions have a negative impact on economic efficiency. However, in the spirit of Topel (1998), we remain skeptical about what the data to date have told us about the specifics of the labor demand equation, especially with regard to firing costs. In our view, the extensive empirical macro- and micro-level literature on the impact of these provisions is largely inconclusive, as are the results we and others have obtained for Chile using statistics based directly on the labor demand equation.

We argue that the mixed evidence is a consequence of the weak power of statistics being used. We develop a dynamic theory of labor demand in the face of firing costs. It points to many potential problems that can lead to low or no power for statistics derived directly from the labor demand equation.

Our theory is clear on one issue: firing costs drive a wedge between the marginal revenue product of labor and its marginal cost. We develop a new test statistic, showing how to directly estimate this gap using plant-level production data. Our statistic has a clear link to welfare, is easy to compute, and is robust to many of the aggregation and estimation problems that afflict the more traditional statistics. There also exist many "control" inputs whose gaps should not increase in response to firing costs. We find large and statistically significant increases in both the mean and the variance of the within-firm gap between the marginal product of labor and the wage for both white and blue collar workers. We find little positive effect on the mean and variance of gaps for non-labor inputs.

We consider possible future directions. This gap analysis is applicable to many more economic questions beyond the effects of firing costs. Our plant-level gap statistic can be used to look for effects of any policy that introduces additional terms to the plant's first order condition. In terms of the welfare implications, if the gap is increasing, then willingness to pay and cost of production are getting further apart.

We have provided only one empirical example. It remains to be seen whether the gap statistic finds evidence of economic inefficiencies in other plant-level micro datasets where firing costs have changed. These exercises will be possible given the increasing availability of plant-level data and the widespread application of firing costs around the world.

Another direction is to look at data from an industry where markups are known to be important and where information on both demand and supply is available. For example, in the automobile industry, coupling demand and production information together, one could hold constant the markup terms when examining the gaps. These types of case-studies would help to further inform us on the amount of noise added by the markup terms in cases where we suspect markups are important but we do not observe demand side data.

A final question is whether we can aggregate the gaps to a quantity that is tightly linked to changes in aggregate welfare. One way to proceed is to try to recover the value function, from which the labor demand schedule can be derived, as in Aguirregabiria and Alonso-Borrego (1999) and Rota (2004). Together with a model for labor supply and some information on that elasticity, one may be able to formulate a reasonable estimate of this change in welfare. Alternatively, one may be able to use the approach outlined in Petrin and Levinsohn (2005), which relies only on production function estimates, a by-product of the approach outlined here. If a representative agent model is a reasonable approximation to the demand side, they show there is a straightforward relationship between the change in aggregate welfare and the changes in plant-level gaps, when appropriately aggregated.

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A Proofs for Section 2

A.1 Proof of Corollary 1

We prove Corollary 1 by deriving the Euler equations. With periods of non-adjustment, we follow the approach described in Pakes (1994), adding a small amount ϵ to the optimal level of labor at time t and deducting it at the next period of adjustment $t+\tau^*$. Assuming the ϵ-alternative is feasible for all $|\epsilon|$ small enough, this leads to evaluation of the program at $l_t^* + \epsilon$ for all periods up to $t+\tau^*$, and then evaluation at time $t+\tau^*$ at the optimal level $l_{t+\tau^*}$. The difference in profits between the ϵ-alternative and the optimal policy is non-positive in the neighborhood of $\epsilon = 0$. Under weak regularity conditions this difference is differentiable, and the derivative is equal to zero when evaluated at $\epsilon = 0$. We use this result to derive (11) and (12).

For firms that hire, profits under the ϵ-alternative program are

$$\begin{array}{rcl} \theta_t f(l_t^* + \epsilon) & - & w_t(l_t^* + \epsilon) \\ & + & E_t[\sum_{\tau=1}^{\tau^*-1} \beta^\tau (\theta_{t+\tau} f(l_t^* + \epsilon) - w_{t+\tau}(l_t^* + \epsilon))] \\ & + & E_t[\beta^{\tau^*} 1\{l_{t+\tau^*}^* < l_t^*\} \, c \, |l_{t+\tau^*}^* - (l_t^* + \epsilon)|]. \end{array} \tag{21}$$

Subtracting profits earned under the optimal program (with $\epsilon = 0$), taking the derivative with respect to ϵ, and evaluating it at $\epsilon = 0$ yields equation (11).[31]

For firms that fire, profits under the alternative program are

$$\begin{array}{rcl} \theta_t f(l_t^* + \epsilon) & - & w_t(l_t^* + \epsilon) - c\,|(l_t^* + \epsilon) - l_{t-1}^*| \\ & + & E_t[\sum_{\tau=1}^{\tau^*-1} \beta^\tau (\theta_{t+\tau} f(l_t^* + \epsilon) - w_{t+\tau}(l_t^* + \epsilon))] \\ & + & E_t[\beta^{\tau^*} 1\{l_{t+\tau^*}^* < l_t^*\} \, c \, |l_{t+\tau^*}^* - (l_t^* + \epsilon)|]. \end{array} \tag{22}$$

Subtracting profits earned under the optimal program, taking the derivative with respect to ϵ, and evaluating it at $\epsilon = 0$ yields equation (12).#

A.2 Proof of Corollary 2

Using (11) and (12) with $\tau^* = 1$, when $l_t^* > l_{t-1}^*$, l_t^* satisfies

$$\theta_t f'(l_t^*) - w_t - \beta F_{t+1} c = 0, \tag{23}$$

and when $l_t^* < l_{t-1}^*$, l_t^* satisfies

$$\theta f'(l_t^*) - (w_t - c) - \beta F_{t+1} c = 0. \tag{24}$$

Using the implicit function theorem, for firms with $l_t^* > l_{t-1}^*$,

$$\frac{\partial l^*}{\partial c} = \frac{\beta(F_c c + F_{t+1})}{\theta f'' - F_l \beta c}. \tag{25}$$

Similarly, for firms with $l_t^* < l_{t-1}^*$,

$$\frac{\partial l^*}{\partial c} = \frac{\beta(F_c c + F_{t+1}) - 1}{\theta f'' - F_l \beta c}. \tag{26}$$

The claim follows directly. #

[31] For all $|\epsilon|$ in a small enough neighborhood of zero,

$$1\{l_{t+\tau^*}^* < l_t^* + \epsilon\} = 1\{l_{t+\tau^*}^* < l_t^*\},$$

so the derivative of the probability of firing with respect to ϵ is zero in this neighborhood. Accordingly, we have ignored the impact of ϵ on the probability of firing.

A.3 Proof of Lemma 2

We show that $\theta \in \Theta_{c_1}$ implies $\theta \in \Theta_{c_2}$ for $c_2 \geq c_1$, which implies that $Pr(\theta \in \Theta_{c_1}) \leq Pr(\theta \in \Theta_{c_2})$, from which the claim follows.

Fix $\theta \in \Theta_{c_1}$. Consider some $\tilde{l} > l_{t-1}$. Then $\theta \in \Theta_{c_2}$ for $c_2 \geq c_1$ because

$$\begin{array}{ll} \theta f(\tilde{l}) - w\tilde{l} - (\theta f(l_{t-1}) - wl_{t-1}) & \leq \\ C(\tilde{l} - l_{t-1}; c_1) + \beta(\overline{V}(\theta, l_{t-1}; c_1) - \overline{V}(\theta, \tilde{l}; c_1)) & \leq \\ C(\tilde{l} - l_{t-1}; c_2) + \beta(\overline{V}(\theta, l_{t-1}; c_2) - \overline{V}(\theta, \tilde{l}; c_2)) & \end{array} \tag{27}$$

because $C(\tilde{l} - l_{t-1}; c) = 0$ and the Fundamental Theorem of Calculus coupled with $\frac{\partial^2 \overline{V}(\theta, l)}{\partial l \partial c} < 0$ implies

$$\overline{V}(\theta, l_{t-1}; c_1) - \overline{V}(\theta, \tilde{l}; c_1) \leq \overline{V}(\theta, l_{t-1}; c_2) - \overline{V}(\theta, \tilde{l}; c_2).$$

$\tilde{l}$ is arbitrary, so it holds for any value of labor greater than l_{t-1}.

For the same value of θ, consider some $\tilde{l} < l_{t-1}$. In the case, $\frac{\partial C(\tilde{l} - l_{t-1}; c)}{c} = |\tilde{l} - l_{t-1}|$. By assumption this is greater than $\beta|\frac{\partial(\overline{V}(\theta, l_{t-1}; c) - \overline{V}(\theta, \tilde{l}; c))}{\partial c}|$. Integrating from c_1 to c_2 preserves this inequality.#

B Side payment plans that offset firing costs

B.1 Plan 1: Insuring over the worker's life time

Under this plan, wage premia are collected over the worker's tenure with the firm to offset the expected firing costs. The fair premia for worker j is given by α_j, a fraction of annual wages, and is calculated by setting the expected present value of the dismissal costs equal to the present value of the premia collected:

$$\sum_{s=1}^{T} \beta^s \delta_j^s (1-\delta_j)(y_{j,t+s}) = \sum_{s=0}^{T-1} \beta^s \delta_j^s \alpha_j W_j$$

where β is the discount factor, δ_j is the probability of worker j being retained, $y_{j,t+s}$ is the severance cost in annual wages of firing worker j at end of s years, and T is the maximum tenure. Assuming that all workers in a firm have identical wages and dismissal probabilities, we can calculate the drop in wage levels (ie the premium payments) required to offset any increase in dismissal costs. We estimate how large the fall must be to offset the first job security reforms introduced in Chile, assuming the interest rate (for discounting) is 5% and the maximum tenure is 20 years.

Current tenure	Dismissal rate	Implied wage change in year 1
all new	10%	**-3.09%**
all new	15%	**-4.25%**
all new	20%	**-5.19%**
all > 5 years	10%	**-4.17%**
all > 5 years	15%	**-6.25%**
all > 5 years	20%	**-8.33%**

B.2 Plan 2: Insuring period by period over the pool of workers

In this approach, the firm's expected firing cost for each period is insured by collecting a premium from all the workers of the firm. Assuming the same fraction of wages is collected from each worker, the fair premium in this case is obtained by setting:

$$\sum_{j=1}^{N_j} \delta_j y_j = \alpha \sum_{j=1}^{N_j} W_j$$

where δ_j is the probability of worker j being retained, y_{jt} is the severance cost in annual wages of firing worker j and N_j is the number of workers in firm j. Assuming that the workers in the firms are identical, we obtain the required drop in wage levels to pay for the insurance premia that offsets the first increase as:

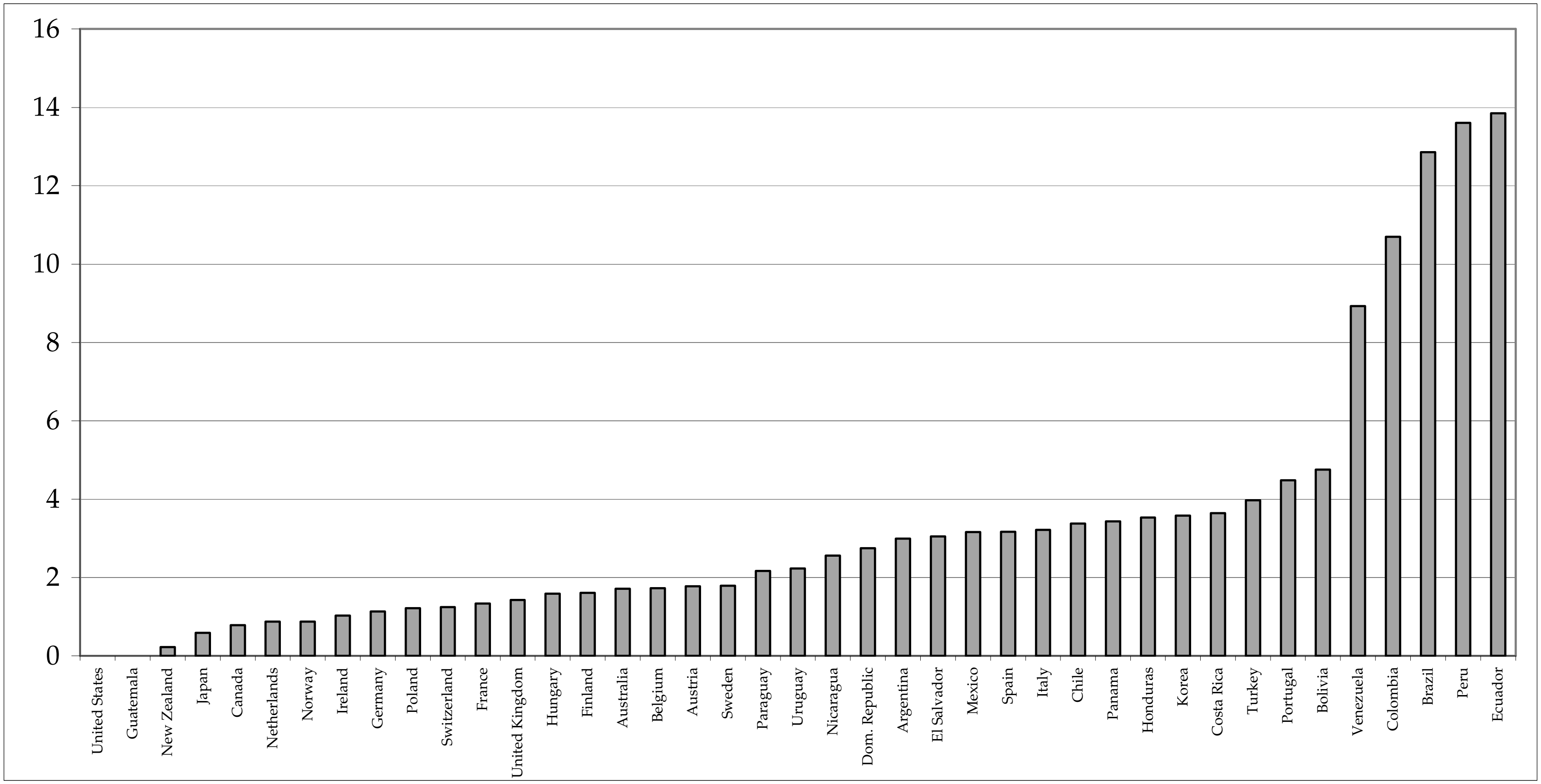
Current tenure	Dismissal rate	Implied wage change in year 1
all new	10%	**-0.83%**
all new	15%	**-1.25%**
all new	20%	**-1.67%**
all > 5 years	10%	**-4.17%**
all > 5 years	15%	**-6.25%**
all > 5 years	20%	**-8.33%**

If workers are identical and $y_{j,t+s}$ is constant over all j (as in the case where the tenure of all workers exceeds 5 years), the premium payments are the same for both plans and given by $(1-\delta)y$.

Since we expect the current average tenure of typical firm to be between the extremes considered in the tables above, we guess that the fall in wages required to neutralize the Chilean 1984 dismissal cost might lie in the range of 3% to 6%. The second job security change increases the maximum dismissal cost from 5 months to 11 months, implying an additional drop that is similar in magnitude.

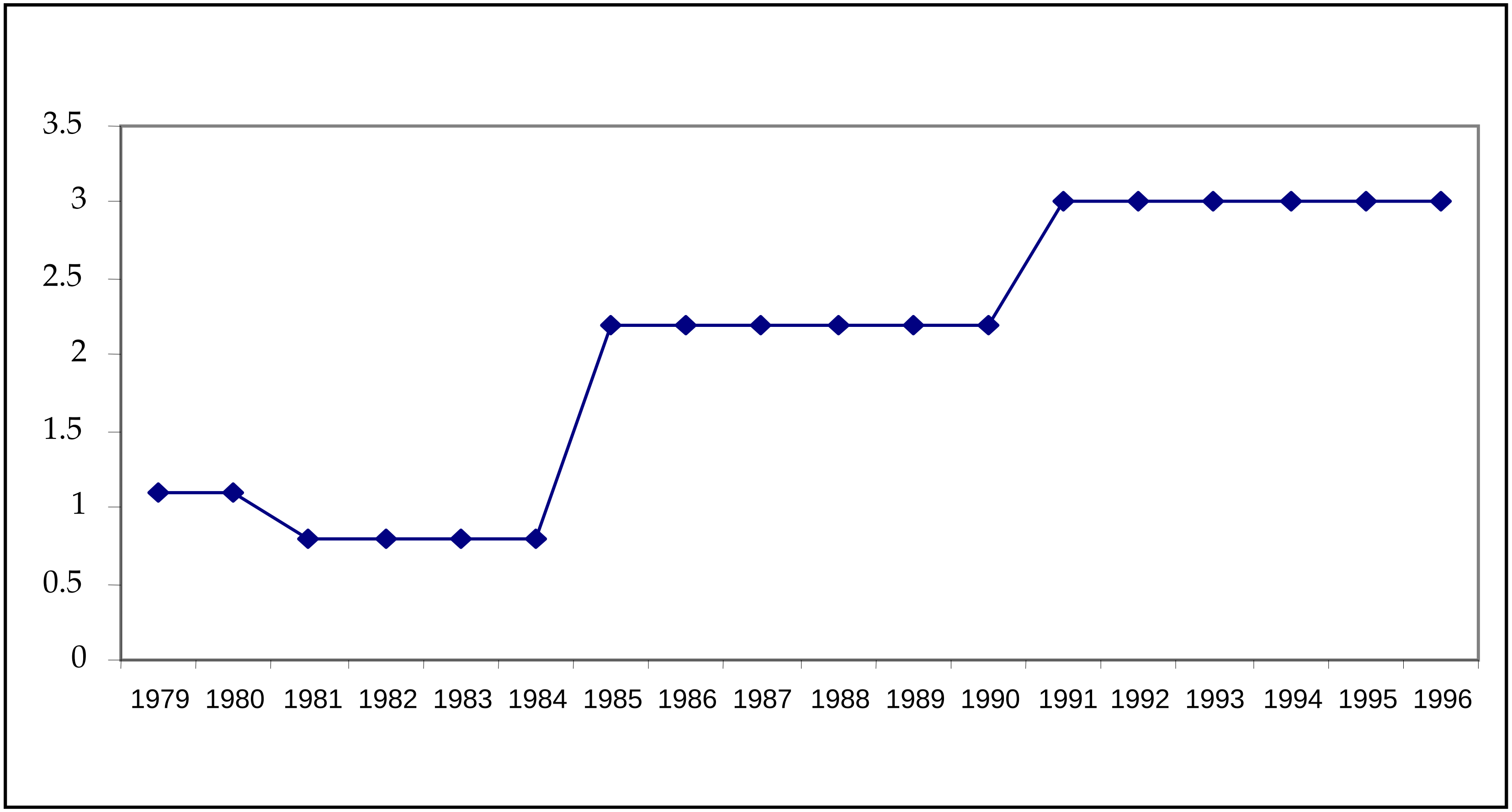
Figure 1
Expected Discounted Cost of Firing a Worker

Multiples of Monthly Wages, Latin America and the OECD Countries, 1999



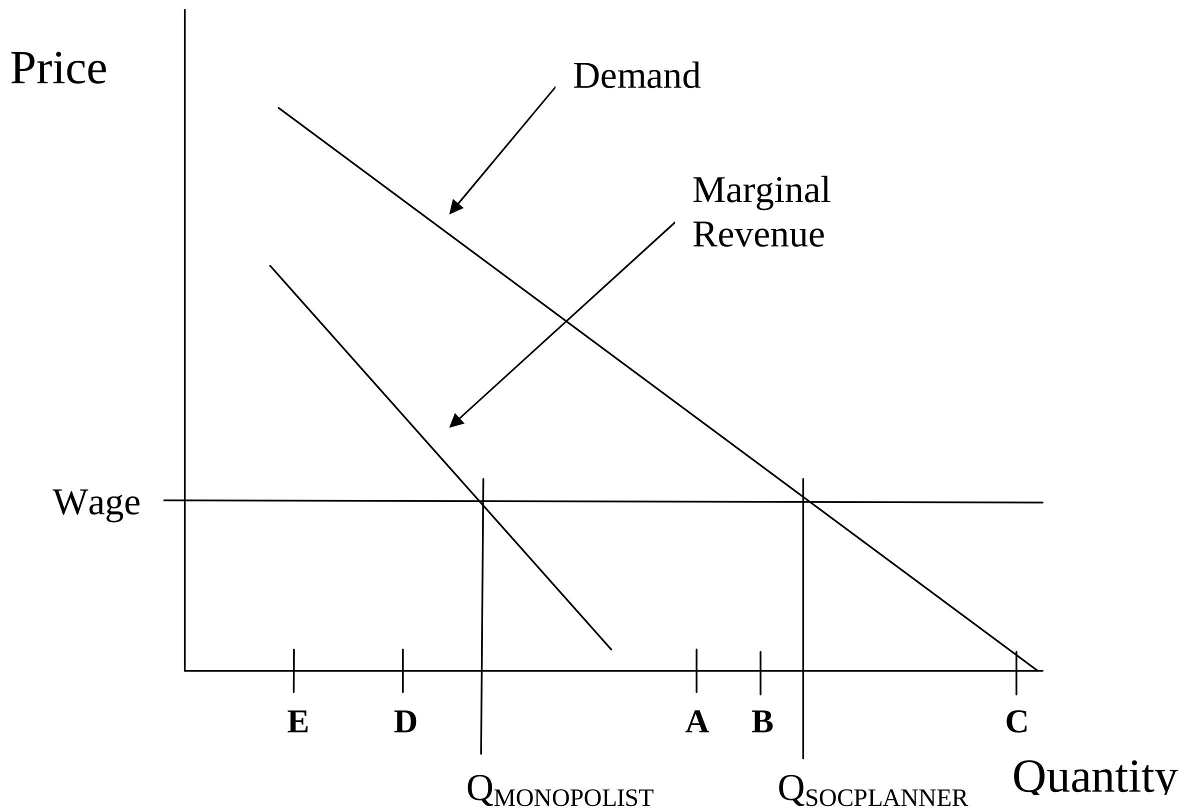
Source: Heckman and Pages (2004). Firing costs are defined as the additional payment made to the worker at the time of dismissal. This definition does not include ``indirect" payments, like those made by U.S. firms into an insurance fund based in part on the number of firings at the firm.

Figure 2
The Change in Firing Costs in Chile
Expected discounted cost of dismissing a worker, in multiples of monthly wages



Source: Pages and Montenegro (1999).

Figure 3
Relating Changes in Gaps to Changes in Welfare



$Q_{monopolist}$ sets marginal revenue equal to wage, while $Q_{socplanner}$ sets demand equal to wage. In a competitive setting (no markups) we recover the difference between the demand curve and input marginal cost (wage). In this case, if the absolute value of the gap increases then economic efficiency decreases, as in a move from B to A or B to C. When there are markups we recover the gap between the marginal revenue curve and marginal cost (wage). In this case we can only sign the change in economic efficiency for firms that have positive gaps (i.e. to the left of $Q_{monopolist}$). For example, welfare unambiguously decreases if we move from D to E.

Table 1
The Absolute Value of the Gap
Between the Marginal Revenue Product and the Input Price, 1979-1996
All Specifications Include Plant-level Fixed Effects

Simultaneity-Corrected Production Function Estimates, Standard Errors in Brackets

	Blue Collar		White Collar		Materials		Electricity	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Base Period Gap (1979-1984)	99.11	99.31	175.48	175.99	0.31	0.31	7.56	7.59
	[4.53]**	[4.53]**	[4.48]**	[4.50]**	[0.01]**	[0.01]**	[0.28]**	[0.28]**
Increase in Gap, 2nd Pd. (85-90)	20.99	20.68	9.51	8.69	-0.04	-0.04	-1.11	-1.15
	[4.41]**	[4.42]**	[5.87]	[5.89]	[0.01]**	[0.01]**	[0.33]**	[0.34]**
Increase in Gap, 3rd Pd. (91-96)	33.02	32.74	15.56	14.83	-0.02	-0.01	-1.57	-1.61
	[7.95]**	[7.97]**	[6.86]*	[6.89]*	[0.01]*	[0.01]*	[0.40]**	[0.41]**
Industry Output Growth Rate		2.01		5.16		-0.01		0.29
		[1.35]		[3.41]		[0.01]+		[0.19]
Observations	54,230	54,226	54,269	54,265	55,329	55,325	55,329	55,325
R-squared	0.81	0.81	0.67	0.67	0.69	0.69	0.71	0.71

All variables are in thousands of 1979 pesos. We focus on the absolute value of the gap because increases in the gap are associated with decreases in economic efficiency (see Figure 3). Marginal product estimates are from a gross output Cobb-Douglas production function specification, which is estimated using Levinsohn-Petrin (2002) to address the simultaneous determination of inputs and productivity. The blue-collar input price is the total blue-collar wage bill divided by the number of blue-collar employees. We define the other input prices similarly. We estimate production functions separately for each 3-digit industry. We cluster standard errors at the 4-digit industry-period level. + significant at 10%; * significant at 5%; ** significant at 1%.

Table 2
Average Dispersion of the Within-Firm Gap
Between the Marginal Revenue Product and the Input Price, 1979-1996
All Specifications Include Plant-level Fixed Effects
Simultaneity-Corrected Production Function Estimates, Standard Errors in Brackets

	Blue Collar		White Collar		Materials		Electricity	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Base Period Gap (1979-1984)	102.71	102.87	144.67	145.07	0.26	0.26	7.13	7.15
	[2.97]**	[2.98]**	[3.05]**	[3.06]**	[0.01]**	[0.01]**	[0.16]**	[0.16]**
Increase in Gap, 2nd Pd. (85-90)	20.91	20.67	13.79	13.16	-0.04	-0.04	-0.97	-1.00
	[3.48]**	[3.49]**	[3.68]**	[3.704]**	[0.01]**	[0.01]**	[0.18]**	[0.19]**
Increase in Gap, 3rd Pd. (91-96)	43.29	43.08	25.7	25.14	-0.02	-0.02	-1.19	-1.21
	[5.02]**	[5.04]**	[4.787]**	[4.798]**	[0.004]**	[0.004]**	[0.23]**	[0.23]**
Industry Output Growth Rate		1.52		3.99		-0.01		0.17
		[1.09]		[2.46]		[0.01]+		[0.12]
Observations	54,230	54,226	54,269	54,265	55,329	55,325	55,329	55,325
R-squared	0.76	0.76	0.60	0.60	0.63	0.63	0.58	0.58

All variables are in thousands of 1979 pesos. We measure dispersion by predicting expected plant-year gaps by regressing observed plant-level gaps used in Table 1 on plant fixed effects and two indicator variables that allow changes in firing cost to affect the prediction, one for 1985-1990, and one for 1991-1996. We then deduct the prediction from the observed plant-level gap, and take the absolute value. We cluster standard errors at the 4-digit industry-period level. + significant at 10%; * significant at 5%; ** significant at 1%.

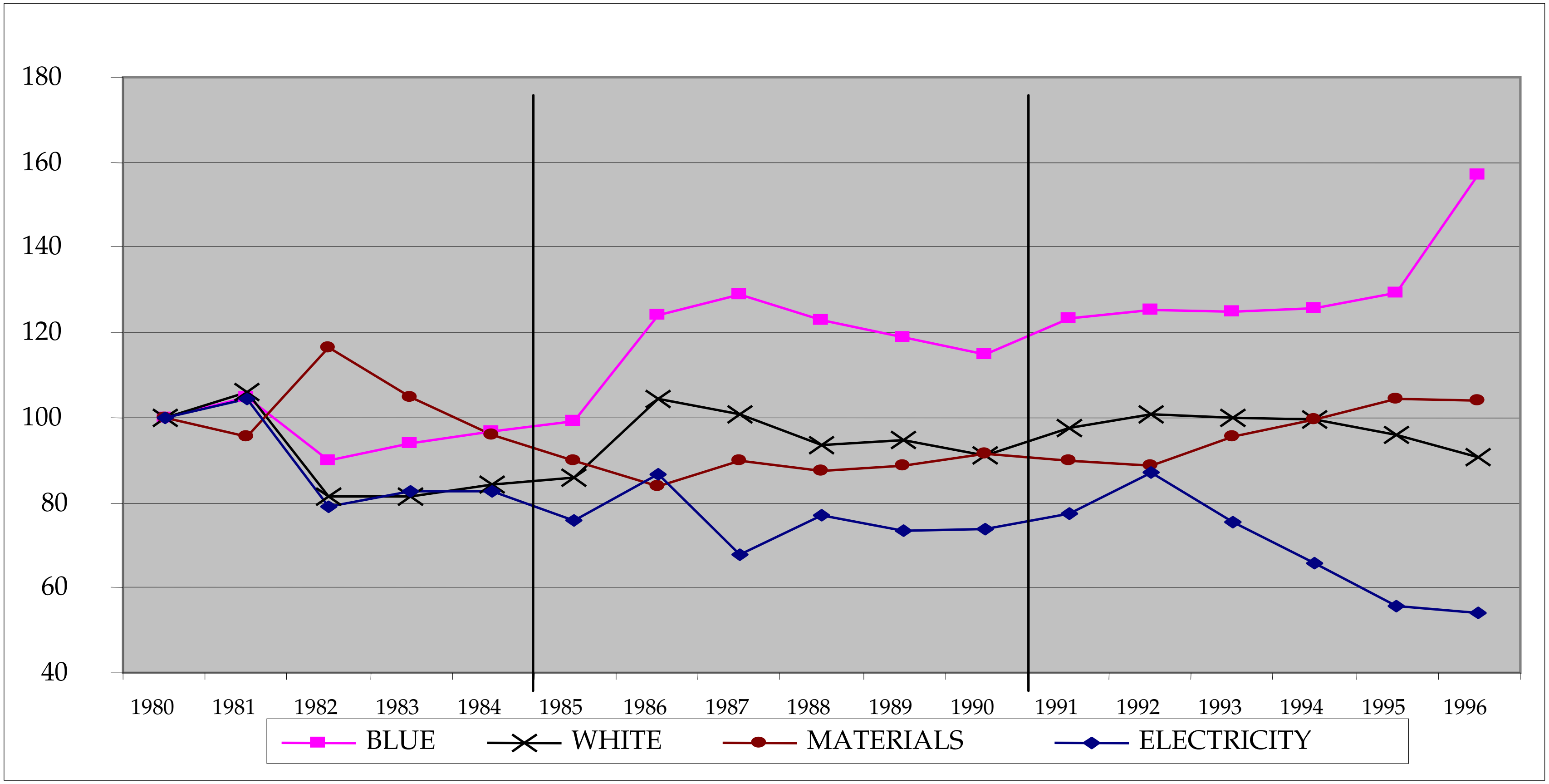
Table 3
The Gap between the Marginal Revenue Product and the Input Price, 1979-1996
All Specifications Only Use Plants with Positive Gaps in Juxtaposed Time-Periods to Allow for Markups
All Specifications Include Plant-level Fixed Effects

Simultaneity-Corrected Production Function Estimates, Standard Errors in Brackets

	Blue Collar		White Collar		Materials		Electricity	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Base Period Gap (1979-1984)	113.66	114.72	197.63	198.21	0.44	0.44	8.24	8.27
	[5.62]**	[5.59]**	[6.77]**	[6.79]**	[0.01]**	[0.01]**	[0.29]**	[0.29]**
Increase in Gap, 2nd Pd. (85-90)	30.47	28.47	28.34	27.33	-0.09	-0.08	-1.21	-1.26
	[5.27]**	[5.21]**	[7.65]**	[7.67]**	[0.01]**	[0.01]**	[0.34]**	[0.35]**
Increase in Gap, 3rd Pd. (91-96)	46.92	45.23	33.15	32.26	-0.03	-0.03	-1.70	-1.74
	[9.78]**	[9.76]**	[10.55]**	[10.59]**	[0.01]**	[0.01]**	[0.41]**	[0.42]**
Industry Output Growth Rate		14.32		7.10		-0.01		0.30
		[3.87]**		[4.45]		[0.01]		[0.20]
Observations	37,923	37,921	38,167	38,165	28,647	28,644	50,519	50,515
R-squared	0.79	0.79	0.7	0.7	0.71	0.71	0.7	0.7

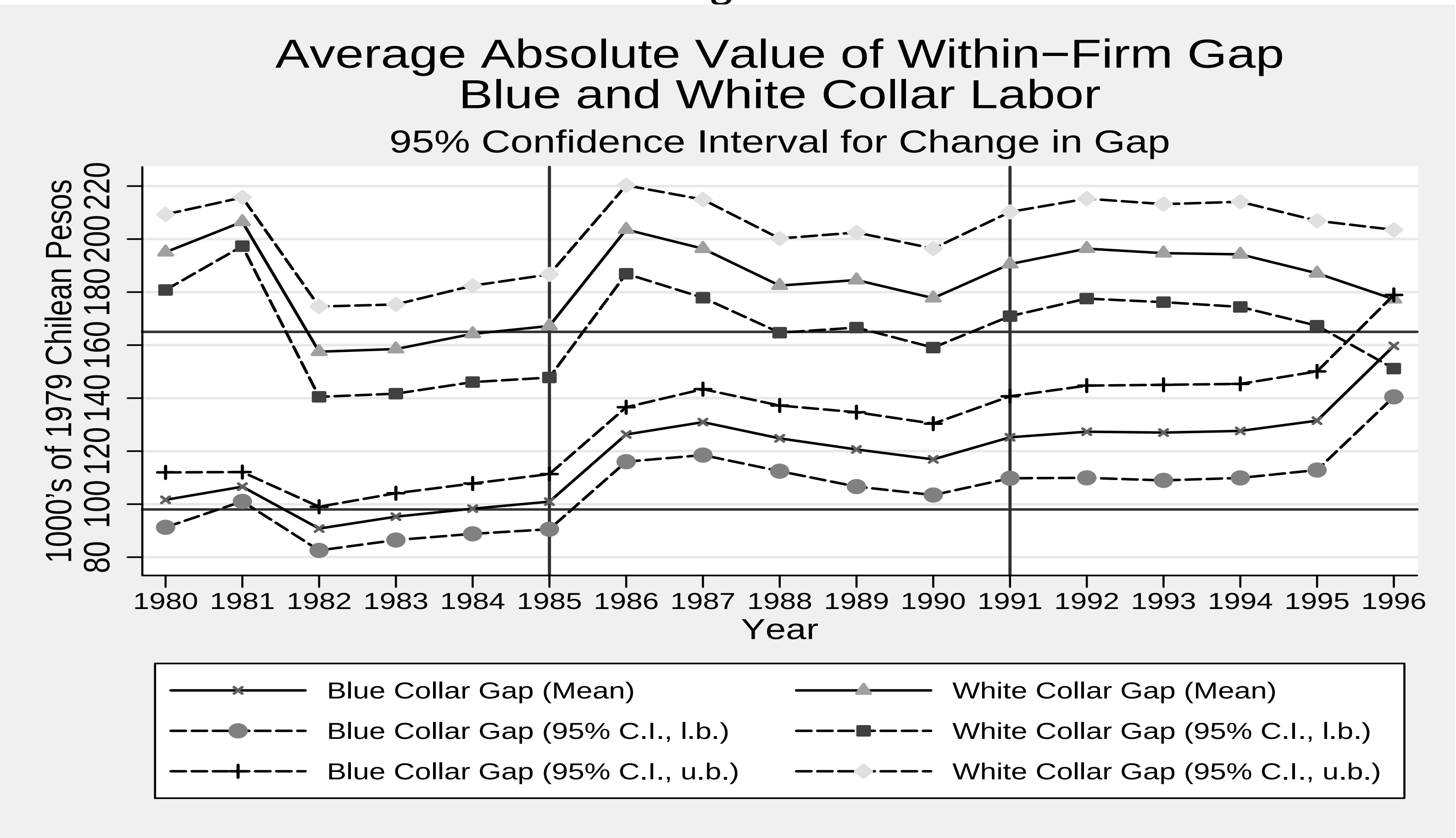
All variables are in thousands of 1979 pesos. If markups exist, our focus should be on only those firms with positive gaps *in juxtaposed time-periods.* Increases in the value of the gap for these firms are associated with decreases in economic efficiency (see Figure 3). Marginal product estimates are from a gross output Cobb-Douglas production function specification, which is estimated using Levinsohn-Petrin (2002) to address the simultaneous determination of inputs and productivity. The blue-collar input price is the total blue-collar wage bill divided by the number of blue-collar employees. We define the other input prices similarly. We estimate production functions separately for each 3-digit industry. We cluster standard errors at the 4-digit industry-period level. + significant at 10%; * significant at 5%; ** significant at 1%.

Figure 4
Year-to-Year Differences in the Absolute Gap
Blue and White Collar Labor, Materials, and Electricity
Levinsohn-Petrin Production Function Estimates



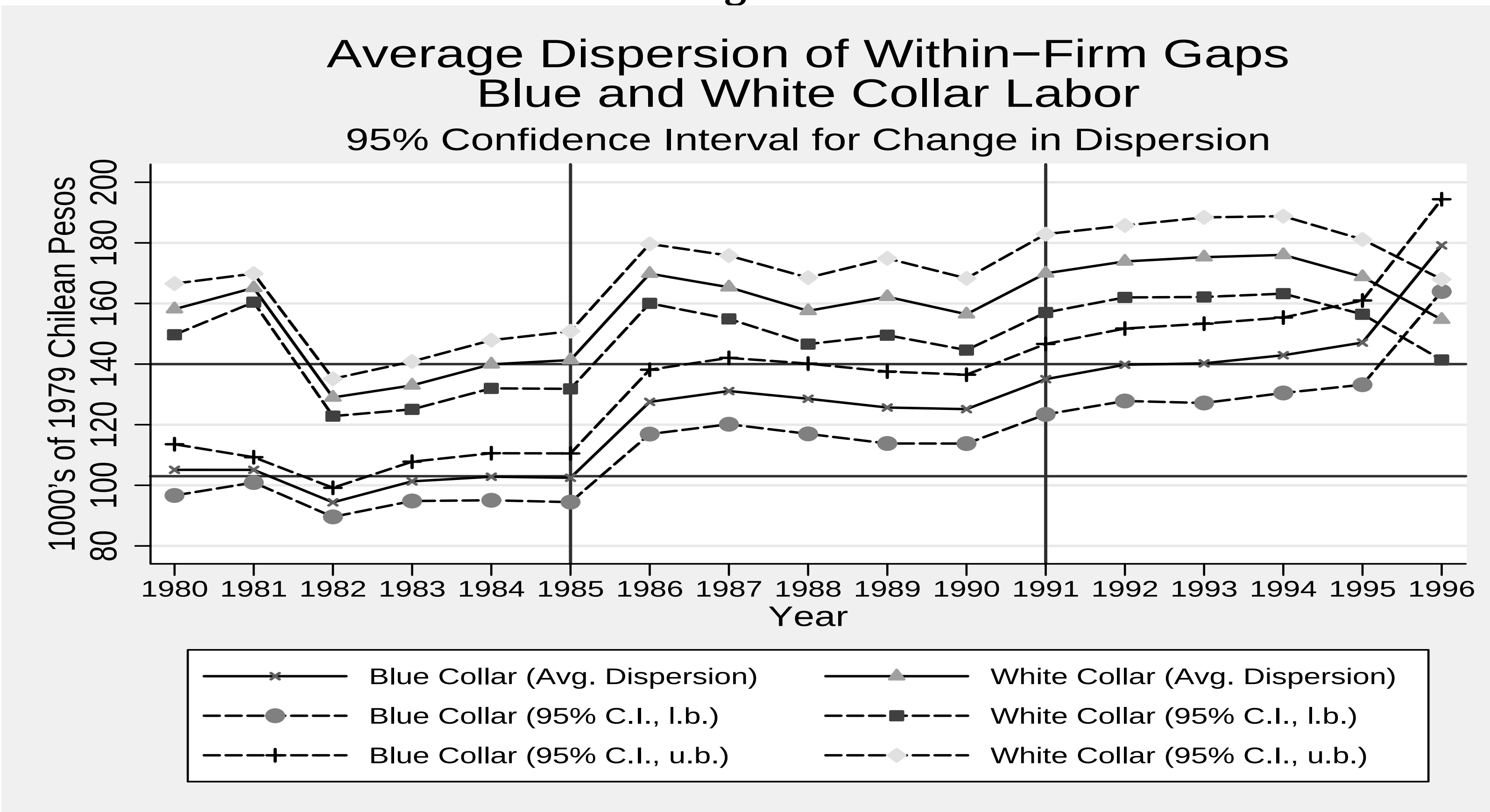
The graph plots the coefficient on year dummies in regression of absolute gap between marginal product of an input and its normalized price. The regression includes firm fixed effects and industry output growth rate. Year 1980 is normalized to 100.

Figure 5



Gaps are those implied by the Levinsohn-Petrin Estimator. The figure plots the coefficients from the regression of the absolute value of the gaps on yearly indicator variables, plant-level fixed effects, and the percentage change in the industry growth rate. The two lines demark the level of the average gap for blue and white collar labor in 1984, so the years for which the line is not within the confidence interval are the years for which the change in the gap is significantly different from the 1984 gap.

Figure 6



We measure dispersion by predicting expected plant-year gaps by regressing observed plant-level gaps used in Table 1 on plant fixed effects and two indicator variables that allow changes in firing cost to affect the prediction, one for 1985-1990, and one for 1991-1996. We then deduct the prediction from the observed plant-level gap, and take the absolute value. The figure plots the coefficients from the regression of this dispersion on yearly indicator variables, plant-level fixed effects, and the percentage change in the industry growth rate. The two lines demark the level of the average dispersion for blue- and white- collar labor in 1984, so the years for which the line is not within the confidence interval are the years for which the change in the gap is significantly different from the 1984 gap.

Table 4
Labor Demand Regression
Blue Collar Employment, Instrumental Variables

	Blue Collar Labor			
	Period 1 (1979-84)	Period 2 (1985-90)	Period 3 (1991-96)	All Periods
Constant	-0.01	0.01	-0.04	-0.02
	[0.01]	[0.01]*	[0.01]**	[0.01]**
Blue wage	-0.12	-0.23	-0.10	-0.19
	[0.03]**	[0.02]**	[0.04]*	[0.01]**
Blue wage_t-1	-0.04	0.08	0.23	0.06
	[0.01]**	[0.01]**	[0.02]**	[0.01]**
White wage	0.11	0.02	0.02	0.05
	[0.02]**	[0.01]	[0.01]	[0.01]**
White wage_t-1	-0.02	-0.03	-0.02	-0.04
	[0.01]*	[0.01]**	[0.01]*	[0.01]**
Value added	0.10	-0.01	0.07	0.08
	[0.01]**	[0.02]	[0.01]**	[0.01]**
Value added_t-1	0.04	-0.01	-0.01	0.01
	[0.01]**	[0.01]	[0.01]+	[0.01]**
Blue Employment_t-1	0.12	0.43	0.66	0.45
	[0.05]*	[0.09]**	[0.07]**	[0.05]**
Period Dummy (1985-1990)				0.01
				[0.01]
Period Dummy (1991-1996)				0.01
				[0.01]
Period Dummy (1985-1990)*Blue Employment_t-1				0.35
				[0.10]**
Period Dummy (1991-1996)*Blue Employment_t-1				-0.28
				[0.09]**
Observations	8,129	15,272	18,499	41,900

Dependent variable is the log (Blue Collar Employment). All other variables are also in logs. The regressions are estimated in first differences. The endogenous variables are Blue Wage, White Wage, Value Added and Blue Employment_t-1. Instruments are lagged industry output, lagged industry average Blue Wage, Lagged industry average White Wage, two-period lagged industry output, double lagged industry average blue wage, double lagged industry average white wage, two-period lagged Blue Wage, two-period lagged White Wage, two-period lagged Materials, two-period lagged Capital, two-period lagged Value Added and three-period lagged Blue Collar employment. Standard errors are adjusted for clustering at the 4-digit industry level. + significant at 10%; * significant at 5%; ** significant at 1%.

Table 5
Labor Demand Regression
Blue Collar Employment, Fixed Effects

	Blue Collar Labor			
	Period 1 (1979-84)	Period 2 (1985-90)	Period 3 (1991-96)	All Periods
Constant	1.59	1.55	2.08	0.89
	[0.09]**	[0.18]**	[0.23]**	[0.04]**
Blue wage	-0.15	-0.26	-0.28	-0.23
	[0.02]**	[0.02]**	[0.02]**	[0.01]**
Blue wage_t-1	-0.01	0.06	0.06	0.09
	[0.01]	[0.01]**	[0.01]**	[0.01]**
White wage	0.09	0.06	0.02	0.06
	[0.01]**	[0.01]**	[0.01]	[0.01]**
White wage_t-1	-0.02	-0.01	-0.01	-0.04
	[0.01]**	[0.01]*	[0.01]*	[0.01]**
Value added	0.11	0.10	0.11	0.11
	[0.01]**	[0.01]**	[0.01]**	[0.01]**
Value added_t-1	0.03	0.03	0.01	0.01
	[0.01]**	[0.01]**	[0.01]*	[0.01]**
Blue Employment_t-1	0.22	0.36	0.32	0.55
	[0.01]**	[0.02]**	[0.02]**	[0.01]**
Period Dummy (1985-1990)				-0.03
				[0.01]*
Period Dummy (1991-1996)				-0.02
				[0.01]
Period Dummy (1985-1990)*Blue Employment_t-1				0.02
				[0.01]**
Period Dummy (1991-1996)*Blue Employment_t-1				0.02
				[0.01]**
Observations	17,650	20,416	23,155	61,221
R-squared	0.95	0.95	0.94	0.93

Dependent variable is the log (Blue Collar Employment). All other variables are also in logs. Standard errors are adjusted for clustering at the 4-digit industry level. + significant at 10%; * significant at 5%; ** significant at 1%.

Table 6
Probability of Not Adjusting Labor

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.179	0.179	0.146	0.146	0.172	0.17
	[0.013]**	[0.013]**	[0.006]**	[0.007]**	[0.023]**	[0.032]**
Period dummy (1985-1990)	-0.044	-0.044	-0.003	-0.003	0.001	0.012
	[0.008]**	[0.008]**	[0.009]	[0.009]	[0.011]	[0.011]
Period dummy (1991-1996)	-0.044	-0.044	0.009	0.008	0.017	0.036
	[0.006]**	[0.006]**	[0.010]	[0.010]	[0.015]	[0.018]*
Industry output growth rate		-0.002		0.001		
		[0.003]		[0.003]		
Lagged labor					0	0
					[0.000]**	[0.000]**
Firm wage rate					0	0
					[0.000]	[0.000]+
Observed productivity (LP estimate)					-0.003	
					[0.005]	
Observed productivity (Fixed Effects estimate)						-0.008
						[0.013]
Fixed effects	None	None	Firm	Firm	Firm	Firm
Observations	73,705	73,689	73,705	73,689	55,204	31,891
R-squared	0	0	0.25	0.25	0.24	0.25
Number of clusters	89	89	89	89	60	84

Dependent variable is one if the firm does not adjust its total employment level from the previous year. All other variables are in logs. Standard errors are adjusted for clustering at the 4-digit industry level. + significant at 10%; * significant at 5%; ** significant at 1%.

Table 7
Firing Rates Conditional on Firing
Percentage change

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.172	0.17	0.174	0.169	0.232	0.208
	[0.005]**	[0.005]**	[0.004]**	[0.003]**	[0.026]**	[0.022]**
Period dummy (1985-1990)	-0.019	-0.016	-0.025	-0.019	-0.034	-0.03
	[0.005]**	[0.005]**	[0.008]**	[0.007]**	[0.010]**	[0.013]*
Period dummy (1991-1996)	-0.026	-0.023	-0.026	-0.02	-0.057	-0.06
	[0.004]**	[0.004]**	[0.005]**	[0.004]**	[0.010]**	[0.014]**
Industry output growth rate		-0.011		-0.025		
		[0.005]*		[0.006]**		
Lagged labor					0.00	0.00
					[0.000]**	[0.000]**
Firm wage rate					0.00	0.00
					[0.000]**	[0.000]**
Observed productivity (LP estimate)					-0.02	
					[0.006]**	
Observed productivity (Fixed Effects estimate)						-0.028
						[0.007]**
Fixed effects	None	None	Firm	Firm	Firm	Firm
Observations	28,908	28,898	28,908	28,898	21,216	12,557
R-squared	0.01	0.01	0.37	0.37	0.39	0.410
Number of clusters	89	89	89	89	60	81

Firing rate is the absolute percentage decrease in employment over the previous year, defined for firms that decrease employment. Standard errors are adjusted for clustering at the 4-digit industry level. + significant at 10%; * significant at 5%; ** significant at 1%.

Table 8
Hiring Rates Conditional on Hiring
Percentage Changes

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.244	0.244	0.258	0.258	0.297	0.269
	[0.011]**	[0.011]**	[0.007]**	[0.007]**	[0.024]**	[0.033]**
Period dummy (1985-1990)	-0.012	-0.013	-0.023	-0.023	0.014	0.023
	[0.006]+	[0.006]*	[0.007]**	[0.007]**	[0.006]*	[0.007]**
Period dummy (1991-1996)	-0.045	-0.046	-0.074	-0.074	0.004	0.026
	[0.010]**	[0.010]**	[0.013]**	[0.013]**	[0.013]	[0.009]**
Industry output growth rate		0.01		0.004		
		[0.007]		[0.005]		
Lagged labor					0.00	0.00
					[0.000]**	[0.000]**
Firm wage rate					0.00	0.00
					[0.000]**	[0.000]**
Observed productivity (LP estimate)					0.007	
					[0.005]	
Observed productivity (Fixed Effects estimate)						0.02
						[0.014]
Fixed effects	None	None	Firm	Firm	Firm	Firm
Observations	33,903	33,899	33,903	33,899	25,706	14,585
R-squared	0.01	0.01	0.34	0.34	0.39	0.410
Number of clusters	88	88	88	88	59	82

Hiring rate is the percentage change in total employment over previous year, defined for firms that increase employment. Standard errors are adjusted for clustering at the 4-digit industry level. + significant at 10%; * significant at 5%; ** significant at 1%.

Table 9
Explaining Movements in Real Wages

	(1)	(2)	(3)	(4)	(5)
Period Dummy (1985-1990)	-0.37	-0.37	-0.40	-0.36	-0.53
	[0.02]**	[0.02]**	[0.02]**	[0.02]**	[0.02]**
Period Dummy (1991-1996)	0.08	0.07	-0.007	0.09	-0.11
	[0.02]**	[0.02]**	[0.02]	[0.02]**	[0.02]**
Firm Output Growth Rate		0.008			
		[0.002]**			
Log(Industry Output)			0.12		
			[0.02]**		
Industry Output Growth Rate				0.001	
				[0.006]	
Unemployment Rate					-2.13
					[0.19]**
Constant	4.49	4.52	2.52	4.48	4.81
	[0.01]**	[0.01]**	[0.31]**	[0.01]**	[0.02]**
Observations	86,176	73,701	86,160	80,346	86,176
R-squared	0.8	0.82	0.81	0.81	0.81
Number of clusters	89	89	89	89	89

Dependent variable is Log (real wage rate). Real wage rate is the nominal wage rate deflated by the producer price index. Nominal wage rate is defined as the total wage bill/ number of employees. For each independent variable the first row gives the coefficient values and the second row gives the related t-values. All regressions include firm fixed effects. Standard errors are adjusted for clustering at the 4-digit industry level. + significant at 10%; * significant at 5%; ** significant at 1%.

Table A1
The Absolute Value of the Gap
Between the Marginal Revenue Product and the Input Price, 1979-1996
All Specifications Include Plant-level Fixed Effects

Fixed Effects Production Function Estimates

Standard Errors in Brackets

	Blue Collar		White Collar		Materials		Electricity	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Base Period Gap (1979-1984)	112.39	112.73	167.71	168.11	0.30	0.30	6.72	6.75
	[5.02]**	[5.03]**	[3.63]**	[3.68]**	[0.01]**	[0.01]**	[0.13]**	[0.13]**
Increase in Gap, 2^{nd} Pd. (85-90)	27.78	27.19	9.62	8.89	-0.03	-0.03	-0.89	-0.92
	[6.11]**	[6.10]**	[4.87]+	[4.93]+	[0.01]**	[0.01]**	[0.14]**	[0.14]**
Increase in Gap, 3rd Pd. (91-96)	37.18	36.67	14.13	13.48	-0.02	-0.02	-1.4	-1.44
	[7.92]**	[7.93]**	[5.83]*	[5.89]*	[0.01]**	[0.01]**	[0.19]**	[0.19]**
Industry Output Growth Rate		3.04		4.30		-0.01		0.22
		[1.83]		[2.45]+		[0.01]+		[0.13]
Observations	60,796	60,781	60,824	60,809	62,287	62,272	62,287	62,272
R-squared	0.81	0.81	0.68	0.68	0.67	0.67	0.70	0.70

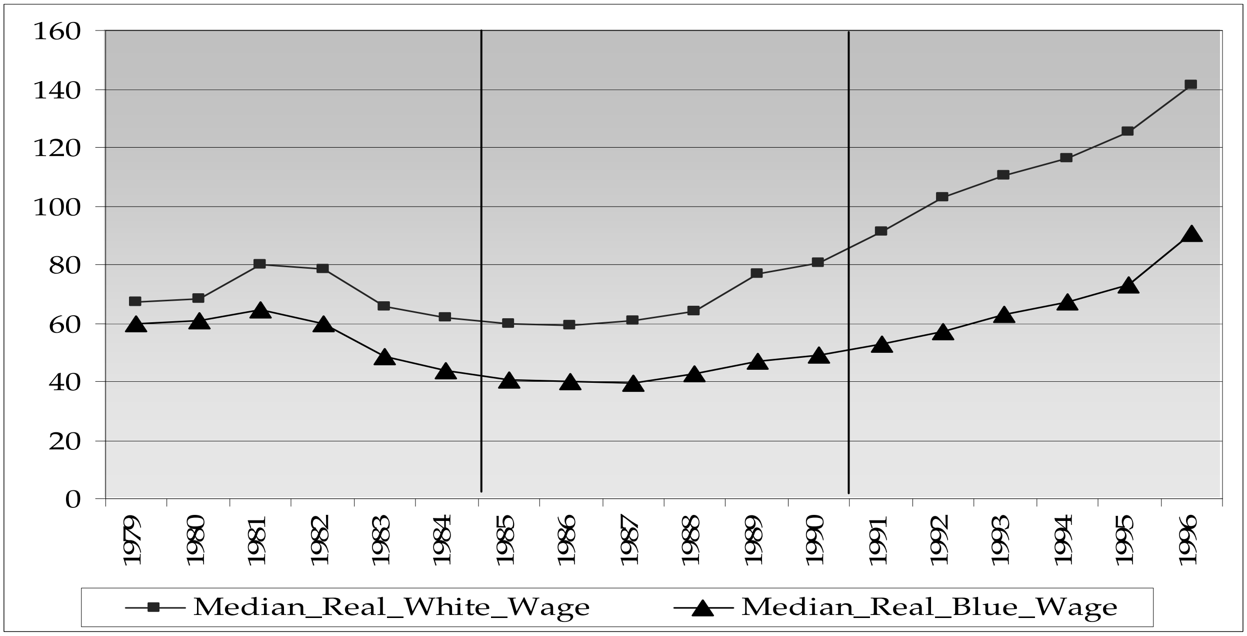
All variables are in thousands of 1979 pesos. We focus on the absolute value of the gap because increases in the gap are associated with decreases in economic efficiency (see Figure 3). Marginal product estimates are from a gross output Cobb-Douglas production function specification, which is estimated using a fixed effects estimator to address the simultaneous determination of inputs and productivity. The blue-collar input price is the total blue-collar wage bill divided by the number of blue-collar employees. We define the other input prices similarly. We estimate production functions separately for each 3-digit industry. We cluster standard errors at the 4-digit industry-period level. + significant at 10%; * significant at 5%; ** significant at 1%.

Table A2
Labor Demand Regression
Blue Collar Employment, OLS

	OLS			
	Period 1 (1979-84)	Period 2 (1985-90)	Period 3 (1991-96)	All Periods
Constant	0.17	0.08	0.09	0.14
	[0.03]**	[0.02]**	[0.03]**	[0.01]**
Blue wage	-0.19	-0.27	-0.29	-0.25
	[0.01]**	[0.01]**	[0.02]**	[0.01]**
Blue wage_t-1	0.09	0.17	0.20	0.15
	[0.01]**	[0.01]**	[0.01]**	[0.01]**
White wage	0.08	0.05	0.04	0.06
	[0.01]**	[0.01]**	[0.01]**	[0.01]**
White wage_t-1	-0.08	-0.04	-0.03	-0.05
	[0.01]**	[0.01]**	[0.01]**	[0.01]**
Value added	0.10	0.10	0.12	0.11
	[0.01]**	[0.01]**	[0.01]**	[0.01]**
Value added_t-1	-0.03	-0.02	-0.04	-0.03
	[0.01]**	[0.01]**	[0.01]**	[0.01]**
Blue Employment_t-1	0.85	0.87	0.88	0.85
	[0.01]**	[0.01]**	[0.01]**	[0.01]**
Period Dummy (1985-1990)				-0.04
				[0.01]**
Period Dummy (1991-1996)				-0.05
				[0.01]**
Period Dummy (1985-1990)*Blue Employment_t-1				0.02
				[0.003]**
Period Dummy (1991-1996)*Blue Employment_t-1				0.01
				[0.004]**
Observations	17,650	20,416	23,155	61,221
R-squared	0.91	0.92	0.9	0.91

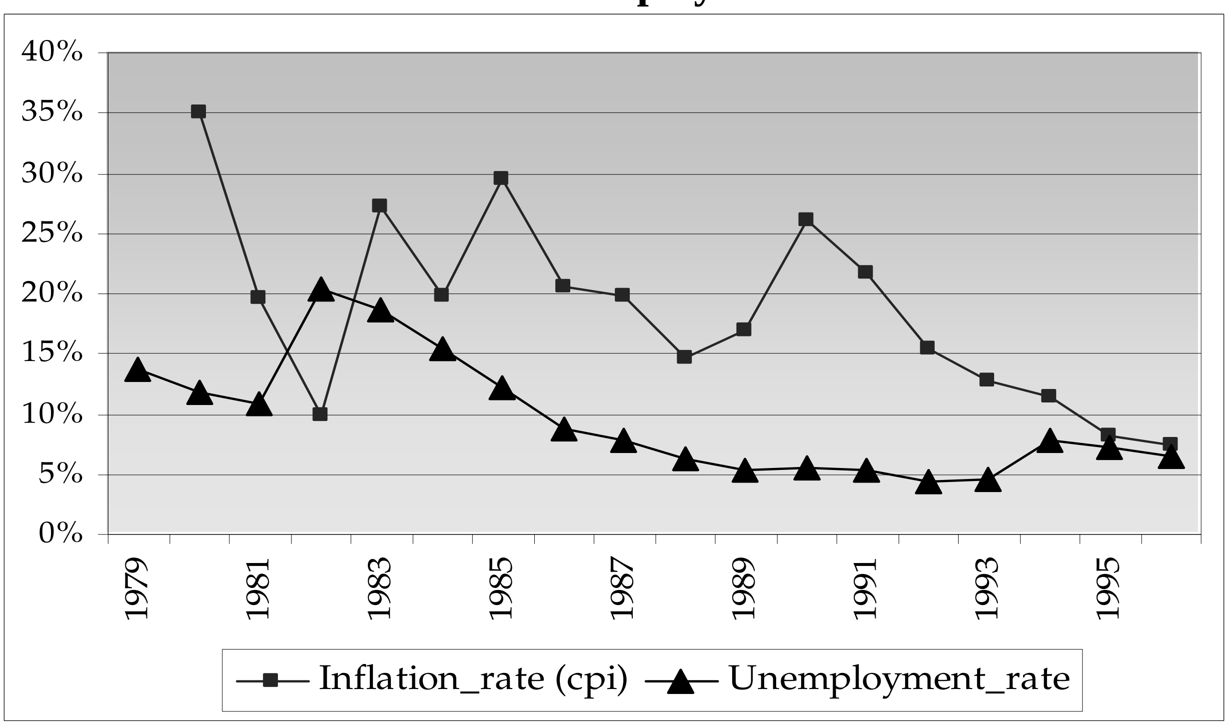
Dependent variable is the log (Blue Collar Employment). All other variables are also in logs. Standard errors are adjusted for clustering at the 4-digit industry level. + significant at 10%; * significant at 5%; ** significant at 1%.

Figure A1
Trends in Real Wages



Source: Authors' calculations

Figure A2
Inflation and Unemployment Rate



Source: Edwards & Edwards (2000), ILO statistics, authors' calculations.