Volatility, Distortions and Labor Misallocation

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July, 2014

Abstract

This paper examines the relationship between aggregate labor productivity dispersion, adjustment costs and the volatility of shocks. A growing literature has identified the extent of misallocation from the variation in inputs' marginal productivity across establishments. The available estimates suggest that improvements in resource allocation can bring about large total factor productivity gains. This literature, however, typically equates productivity dispersion with explicit policies that favor some firms over others. In this paper we claim that an important additional factor behind productivity dispersion is a volatile environment combined with adjustment costs. After a shock, firms that face adjustment costs experience a temporary gap between the value of inputs' marginal productivity and their market price. The higher adjustment costs and volatility are the higher nominal productivity dispersion is. Using plant-level data for the Chilean manufacturing sector, we analyze the evolution of labor productivity dispersion over years 1990 to 2007. We relate this evolution to changes in the speed of adjustment of firms and changes in the volatility of the shocks firms face. In explaining labor productivity dispersion, we empirically find a role for both the speed at which firms adjust their employment levels and the volatility of the credit, energy and exchange rate markets, i.e., the uncertainty of the operating environment.

Keywords: Labor productivity, productivity dispersion, adjustment costs, Chilean manufacturing.

JEL Codes: D24, O12, O47.

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I. Introduction

Recent empirical studies suggest that resource misallocation can explain a relevant part of the observed total factor productivity (TFP) gaps between rich and poor countries (see Restuccia and Rogerson 2013, for a recent survey). In an economy with heterogeneous production units, there are two main sources of resource misallocation at any given point in time: distortions and shocks in the presence of adjustment costs.

In an economy with no distortions, the allocation of inputs leads to the equalization of the value of marginal productivity across production units, and output net of fixed costs is maximized. The introduction of subsidies, tax exemptions, uneven regulatory burdens and other institutional factors, end up distorting the optimal allocation of resources. Hopenhayn and Rogerson (1993), Restuccia and Rogerson (2008) and Hsieh and Klenow (2009) are examples of this view: they show how taxes and specific policies distort the allocation of inputs across establishments and lead to aggregate TFP losses. Since these distortions do not vanish over time —unless there are regulatory revisions that remove them—along this paper we call them “static distortions”.

Micro and macro volatility and adjustment costs also imply that firms do not always produce where the value of marginal productivity of inputs equals market price. Idiosyncratic demand or productivity shocks, for instance, require changes in the optimal level of inputs. Whenever firms cannot adjust instantaneously, heterogeneity in marginal revenue productivity across establishments will be observed. The observed gaps vanish over time as long as firms adjust, and thus we call them “dynamic distortions”. Recently, Asker et al. (2013) have shown that, consistent with the volatility and adjustment costs hypothesis, industries exhibiting greater time-series volatility of productivity display greater cross sectional dispersion of the marginal revenue product of capital.

The static (former) and dynamic (latter) distortions both explain why there may be wide heterogeneity of marginal revenue productivity.[2] Understanding the relative incidence of the factors behind this dispersion, and hence misallocation, is important. On the one hand, greater dispersion could reflect larger policy distortions such as a new set of tax exemptions or a higher incidence of informality that allows some firms to avoid regulatory burdens. Or it could be the result of labor regulation reforms that make employment protection laws more stringent. In all these examples, changes in *de facto* economic policies are behind the greater extent of misallocation.

But this does not need to always be the case. For a given level of *de facto* legal burden, an increase in the volatility of shocks also implies a higher dispersion of marginal productivity as firms take time to adjust. Thus the impact of regulations, laws and adjustment barriers depends on the environment where they are applied.

Moreover, cross-country differences in productivity and resource allocation may partly reflect differences in the extent of economic uncertainty and of adjustment costs. The failure to account for the dynamics of productivity at the plant level and for adjustment lags may lead to an overestimation of the role of market distortions in explaining cross-country TFP differentials. In addition, if productivity uncertainty and adjustment costs are exogenous, the static view may also overestimate the potential welfare and efficiency gains from policy reforms.

In this paper we take advantage of the fact that each type of distortion, static or dynamic, has different empirical implications. Static distortions imply a high persistence of relative marginal revenue differences. A firm that enjoys an input subsidy, for instance, will display a lower level of marginal revenue productivity today and most likely tomorrow. This is not the case with dynamic distortions as dispersion of marginal revenue will evolve over time.

[2] Differences in technology across establishments might also explain heterogeneity in observed productivity but not in marginal revenue productivity (see Hsieh and Klenow 2009). In this paper we focus on changes in the distribution that relate to either these static or dynamic distortions and thus focus the analysis on the extent of misallocation.

A firm that faces a negative shock will display in the short run a lower revenue marginal productivity, but the gap will vanish as long as the firm is able to adjust. How fast the gap disappears depends on the firms' adjustment speed for each production factor.

On the basis of a stylized model, we show that productivity dispersion rises and that aggregate productivity declines with static distortions that favor some firms over others and also with adjustment costs when firms face a volatile environment. Intuitively, from a static perspective, institutions and policies that result in resource misallocation drive wedges between the marginal products of labor across firms, reducing aggregate TFP. From a dynamic perspective, the barriers that delay the adjustment process become more stringent when volatility rises, slowing down the extent at which inputs and outputs reallocate towards the most productive firms, also affecting aggregate TFP.

In our empirical analysis we use plant-level data from the Chilean Industrial Survey (*Encuesta Nacional Industrial Anual*, ENIA) to answer what is behind the observed labor misallocation in Chile on the basis of the evolution of the cross sectional dispersion of productivity. We examine both the role of labor adjustment costs and of changes in the volatility of shocks.

Following Caballero et al. (2013) we first provide estimates of the speed of adjustment of firms at the sector and year levels. We then identify a number of shocks that are relevant determinants of the profits manufacturing firms earn in Chile –shocks to the real exchange rate, to the real interest rate and to the price of oil, and also the magnitude of energy shortages-. We then relate the evolution of labor productivity dispersion at the sector level to the adjustment speed of firms and the volatility of shocks, to find a relevant role for both.

The remainder of this paper is organized as follows. Section II develops a simple model that illustrates the relationship between aggregate productivity and its cross sectional dispersion. It also relates productivity dispersion to static distortions and market volatility when there are adjustment costs. Section III presents the data set, whereas Section IV traces the evolution of manufacturing labor productivity dispersion over years 1990 to 2007. Section V provides estimates of the speed at which plants adjust in Chile. Section VI identifies volatility on the basis of a number of developments occurring in Chilean markets. Section VII correlates productivity dispersion to these developments in the Chilean economy and the evolution of the estimated adjustment costs. Section VIII provides concluding remarks.

II. A Simple Framework

We use a simple adjustment costs model as in Calvo (1983) to describe the effect of static distortions and volatility on aggregate productivity and its dispersion at the industry level. We first solve the model assuming static distortions but no adjustment costs and then we assess how the solution of the model changes with such costs.

Consider an industry where the profits of firm *i* are summarized by the following quadratic function:[3]

$$\Pi(A_{it}, L_{it}) = R(A_{it}, L_{it}) - (1-\tau_i)WL_{it}$$

where

$$R(A_{it}, L_{it}) = A_{it}L_{it} - \tfrac{1}{2}L_{it}^2$$

The function *R* represents firm i's revenues; A_{it} is a profit shifter that summarizes demand and productivity shocks; L_{it} is the firm's level of employment in period t; τ is a static distortion (e.g., a wage or price subsidy), and *W* represents the market wage.

For each firm, A_{it} is a random variable with support $[\underline{A}, \overline{A}]$[4] and cumulative distribution function *F*(*A*), which for simplicity is assumed independent of past values and invariant over time.[5]

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[3] This profit function can be derived assuming linear demand and constant marginal cost functions. Below we also assume that firms are price takers in the labor market.

[4] The parameter $\overline{A}$ is assumed positive.

[5] All results below hold if A_{it} follows an AR(1) process.

Similarly, τ is a zero mean i.i.d. random variable with support $[\underline{t}, \bar{t}]$. We assume $[\underline{A} - W(1- \underline{t})]^{3}\ 0$; that is, once in the market, firms always produce.[6] We also assume that once a firm draws a subsidy from its distribution, the subsidy remains constant.

Finally, the supply of labor is assumed to be infinitely elastic at wage *W*.

No Adjustment Costs

The desired level of employment (the static optimum) without adjustment costs is given by $L_{it}^{*} = A_{it} - (1-\tau_i)W$. Similarly, the expected present value of future profits is given by $\frac{1}{1-\beta}\int \Pi(A, L^{*})dF(A) = \frac{1}{(1-\beta)}\frac{1}{2}E((A_{it} - (1-\tau_i)W)^2)$, where β is the discount factor, *E*() is the expectation operator, and

$$E((A_{it} - (1-\tau_i)W)^2) = E\Big((E(A_{it}) - W)^2 + \mathrm{var}(A_{it}) + W^2\,\mathrm{var}(\tau_i)\Big).$$

In this setup, (*A*-*L*) is the firm's marginal revenue or nominal marginal productivity (NPML).[7] Therefore the employment weighted nominal productivity in this economy with static distortions only is given by[8]

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[6] Firm entry could be considered by assuming there is a continuum of firms with different entry costs. In this case firms enter whenever the entry cost is greater or equal than the expected net present value of profits.

[7] We use revenue productivity and productivity interchangeably. This is correct if A_{it} is only driven by productivity shocks. See Foster, Haltiwanger, and Syverson (2008) for a discussion.

[8] To obtain the following result, note that

$$\mathrm{Prod}_t^{Static} \equiv \frac{E((A_{it} - L_{it})L_{it}))}{E(L_{it})} = \frac{E((1-\tau_i)WL_{it}))}{E(L_{it})} = \frac{E((1-\tau_i)W(A_{it} - (1-\tau_i)W)))}{E(L_{it})}$$

$$= \frac{WE(A_{it}) - W^2 - W^2\,\mathrm{var}(\tau_i)}{E(A_{it}) - W} = W - W\,\frac{\mathrm{var}(\tau_i)}{E(A_{it})/W - 1}$$

$$\begin{aligned}\text{Prod}_t^{Static} &\equiv \frac{E((A_{it}-L_{it})L_{it}))}{E(L_{it})} = W - W\,\frac{\text{var}(\tau_i)}{E(A_{it})/W-1} \\ &= \text{Prod}_t^{*} - W\,\frac{\text{var}(\tau_i)}{E(A_{it})/W-1}\end{aligned} \qquad (1)$$

where Prod^{*}_{t} represents aggregate productivity in the absence of distortions. Note also that in this context

$$\text{var}(NPML) \equiv \text{var}((1-\tau)W) = W^2\,\text{var}(\tau)$$

so

$$\text{Prod}^{Static} = \text{Prod}^{*} - \frac{\text{var}(NPML)}{E(A)-W} = \text{Prod}^{*} - \frac{\text{var}(NPML)}{E(L)}$$

This simple model predicts that in an economy with heterogeneous production units and static distortions, aggregate productivity depends negatively on the degree of dispersion of these distortions. In addition, the cross sectional variability of observed productivity rises with the variance of distortions across production units. Moreover, in this fixed and exogenous wage set up, when the economy becomes more volatile -when it experiences a rise in the variance of the profit shifter *A*-, both aggregate productivity and its dispersion remain constant.[9] In what follows, we show that this is not the case when there are adjustment costs.

[9] In a model with a positively sloped labor supply, higher volatility of *A* implies higher Prod^{*} and equilibrium wage.

Adjustment Costs

Now assume an economy populated by heterogeneous firms that face adjustment costs as in Calvo (1983). That is, firms face an exogenously constant probability λ of adjusting their employment levels in a given period.

The value function for a firm with profit parameter A_{it} and employment level L_{it} is now equal to[10]

$$V(A_{it}, L_{it}) = \Pi(A_{it}, L_{it}) + \lambda\beta\int V(A_{it+1}, \tilde{L}_{it+1})dF(A_{it+1}) + (1-\lambda)\beta\int V(A_{it+1}, L_{it})dF(A_{it+1}) \quad (2)$$

where $\tilde{L}_{it+1}$ denotes the dynamic optimal level of employment in firm i in period t+1 given the profit parameter A_{it+1}.

We derive the dynamic optimal level of employment using the first order conditions to obtain

$$\tilde{L}_{it} = (1-\beta(1-\lambda))(A_{it} - (1-\tau_i)W) + \beta(1-\lambda)(E(A_{it+1}) - (1-\tau_i)W) \quad (3)$$

That is, the dynamic optimal level of employment is a weighted average between the current (A_{it} - $(1-\tau_i)$ W) and the expected E(A_{it+1} - $(1-\tau_i)$ W) optimal levels of employment, where the weights are functions of λ and the discount factor β.[11]

Now, in the presence of adjustment costs, the average productivity is given by

$$\text{Prod}^{Dynamic} = \text{Prod}^{*} - (1-\lambda)(1-\beta)(1-\beta(1-\lambda))\frac{\text{var}(A_{it} - W)}{E(A_{it}) - W} - W\frac{\text{var}(\tau_i)}{E(A_{it})/W - 1} \quad (4)$$

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[10] To simplify notation, we omit the dependence on the initial draw of the static distortion τ_i.
[11] $F(A_{it})$ is time invariant; therefore, $E(A_{it+1}-W) = E(A_{it+\theta} - W)$ for any $\theta>0$.

The second term in equation (4) represents the negative impact of adjustment costs in the face of an uncertain environment. Without adjustment costs (λ=1) this term vanishes and equation (4) becomes equation (1). The last term again represents the negative impact on average productivity due to the dispersion introduced by static distortions.

Thus, in the presence of adjustment costs, industry productivity declines as firms face increased volatility. Were λ to be equal to 1 –that is, if adjustments were instantaneous-, then the variance of shocks would not affect aggregate productivity for a given Prod*. Similarly, given the variance of shocks, industry productivity declines whenever adjustment costs increase.

Note that now

$$\mathrm{var}(NPML) \equiv 2(1-\lambda)\big(1-\beta(1-\lambda)(1-\beta)\big)\mathrm{var}(A-W) + W^2\,\mathrm{var}(\tau) \quad (5)$$

That is, the variance of NMPL rises with both the volatility of nominal revenues (*A*) and the dispersion of distortions (τ). Thus omitting the role of shocks and of adjustment costs leads to the overestimation of the extent of misallocation that is driven by static policy distortions. In Section VI below, we estimate empirical models that relate the time evolution of NMPL at the industry level to the speed of adjustment and the variance of shocks firms face.

Replacing *var(A-W)* from equation (5) in equation (4), we can write average productivity as a function of the variance of NMPL:

$$\mathrm{Prod}^{Dynamic} = \mathrm{Prod}^* - \frac{1}{2}\frac{(1-\beta)(1-\beta(1-\lambda))}{1+\beta(1-\lambda)(1-\beta^2/2)}\left(\frac{\mathrm{var}(NMPL)}{E(A)-W} - W^2\,\frac{\mathrm{var}(\tau)}{E(A)-W}\right) - W^2\,\frac{\mathrm{var}(\tau)}{E(A)-W}$$

(6)

If *var(A)* rises, then Prod^{Dynamic} falls for any given Prod*, unless there are no adjustment costs. If $var(\tau)$ rises the term in parentheses does not change (see equation (5)), and the effect on aggregate productivity comes from the last term only.[12]

In other words, industry productivity declines with static distortions that favor some firms over others ($var(\tau)$) but also with adjustment costs when there is volatility ($var(A\text{-}W)$). Intuitively, the barriers that delay the adjustment process become more stringent when volatility rises. This slowdown of the adjustment process reduces the extent at which inputs and outputs reallocate towards the most productive firms, affecting aggregate productivity. Alternatively, marginal productivity across firms diverges as firms do not adjust smoothly to shocks, a signal of the misallocation of inputs and outputs. How large these effects are depend on the size of the adjustment costs ($1\text{-}\lambda$) and the volatility of shocks.

These hypotheses are at the core of our empirical analysis. In the following sections we use manufacturing data at the plant level to first describe the evolution of the dispersion of productivity in Chile. We then analyze whether this evolution is correlated with shifts in the adjustment speed of firms and with the variance of the shocks firms face.

III. The Data

In this paper we use data from the National Annual Manufacturing Industry Survey (*Encuesta Nacional Industrial Anual,* ENIA), an annual survey of manufacturing conducted by the Chilean statistics agency, the *Instituto Nacional de Estadísticas* (INE). The ENIA covers all manufacturing plants employing at least ten individuals. Thus, it includes all newly created and existing plants with ten or more employees, and it excludes plants that

[12] With a positively sloped labor supply, intrinsic sector volatility also increases average productivity because input adjustments allow more productive firms to increase their demand for labor. The average productivity of labor, Prod*, and therefore the equilibrium wage rise, although this process is hampered by adjustment costs.

have ceased activities or reduced their payroll below the survey's threshold. Employment in the ENIA represents about 50% of total manufacturing employment.[13]

The data available extend from 1990 to 2007 and contain detailed information on plant characteristics such as manufacturing sub-sector at the 4-digit ISIC rev.2 level, sales, employment, investment, intermediate inputs and location.[14]

All nominal variables were deflated at the 3-digit ISIC level, using deflators constructed from the wholesale price indices compiled by INE.[15] Our analysis considers all 29 3-digit ISIC rev.2 sectors except copper production (sector 372), as national accounts include copper in the mining sector and not in manufacturing. We have also excluded petroleum refineries –sector 353—from the analysis because of the very small number of plants producing in this sector (at most 10 in any given year).

Table 1 provides basic statistics characterizing plants in our data set over the sample period. The first column presents the number of respondent plants in each year. The next two columns present average value added and gross output expressed in 1992 millions of Chilean pesos.[16] The average wage bill paid is also measured in millions of 1992 Chilean pesos. Employment reported in the fifth column includes all workers in the plant, with no distinction by skill level or type of job. According to ENIA, on average manufacturing value added and output per plant grew at an annual rate near 7% between 1990 and 2007,

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[13]We observe plants and not firms in our data set and thus we are unable to distinguish single-plant firms from multi-plant firms. According to information provided by Central Bank statisticians, about 3.5% of plants belong to a multi-plant firm in our data set.

[14] INE changed the plant identification method in the 1996 survey. Fortunately, we had access to three data bases that allowed us to match up almost all the surveyed plants over time. The 1990-1996 data set and the 1995-2007 set do not have a common identifier, but a third survey set covering the years from 1995 to 2007 had both identifiers for the year 2000. To match up plants that were not in the 2000 survey, we looked for plants that in any given year reported identical values for relevant variables such as wages, number of days in operation, ISIC code, electricity consumed, value added tax (VAT) paid, number of employees, gross output and machinery and equipment investment. For plants that were surveyed in 1995 and 1996 but not in year 2000, we matched up plants by these same variables. Using this method, we were able to match up 97% of plants. We excluded plants for which we could not find an identical match for four or more of these variables.

[15] Most of our results below do not require the use of deflators as we estimate log differences with respect to the average plant in any given sector defined at the 3 digit ISIC rev.2 level.

[16]The average nominal exchange rate in 1992 was equal to 362.7 Chilean pesos per US dollar according to the official statistics of the Central Bank of Chile.

whereas employment and total wages per plant grew at a 1.1% and 3.6% per year, respectively.

As a proxy of the marginal productivity of labor, we use the ratio of value added to the wage bill. We do not directly estimate total factor productivity to avoid imposing the strict conditions that are needed to measure TFP. Following Hsieh and Klenow (2009), we use the wage bill and not employment to approximate the level of human capital within plants. As a robustness check, in our analysis we also estimate the distribution of average productivity using value added over employment at the plant level.[17]

Figure 1 shows the evolution of both aggregate productivity measures over the sample period. On average, between 1990 and 2007 the ratio of value added to employment grew at a 5.7% annual rate, whereas the ratio of value added to the wage bill grew at a 3.6% annual rate. These differences reflect the evolution of wages over the sample period.

Once estimated the evolution of average productivity, we turn to our estimates of its dispersion. To correct for common shocks and differences in productivity across sectors, we estimate the distribution of plant level productivity (in natural logs) relative to the average productivity (also in natural logs) of the plants producing in the same sector and period of time. That is, we estimate the distribution of

$$\ln(VA_{ist} / W_{ist} L_{ist}) - \ln(\sum_{i \in s} \frac{1}{n_{st}} (VA_{ist} / W_{ist} L_{ist}))$$

where VA_{ist} represents value added, W_{ist} wages and L_{ist} employment, all for plant i producing in sector s in year t. In constructing this distribution, we use both weighted and unweighted data. When we do use weights, we weight the gap by the plant's payroll. That is, the weighted distributions presented in Section IV below represent the density of

[17]The results of these robustness exercises are available upon request.

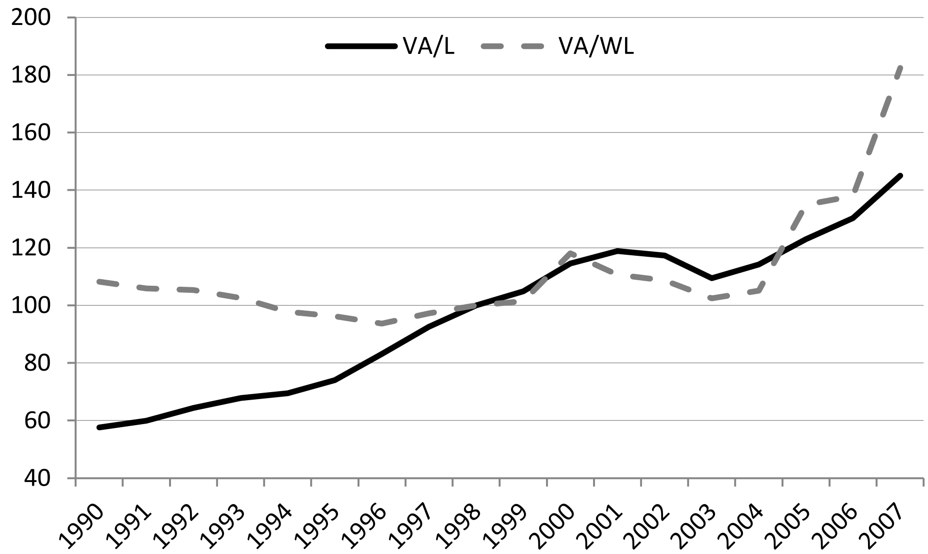
workers' relative productivity in manufacturing in any given year; i.e., the fraction of workers that display a given level of relative productivity.

Table 1. ENIA 1990-2007, Basic Statistics

Year	Number of Plants	Value Added per Plant $92 million	Output per Plant $92 million	Total Employees per Plant	Total Wages per Employee $92 million	Average Deflactor (1992=100)
1990	4289	695	1531	81	1.57	74.9
1991	4424	731	1634	82	1.68	90.2
1992	4651	796	1766	83	1.84	100.0
1993	4743	839	1846	83	2.00	111.7
1994	4759	864	1898	84	2.16	122.4
1995	5053	888	1932	81	2.25	132.5
1996	5293	936	2026	76	2.44	137.4
1997	5095	1056	2218	77	2.65	138.2
1998	4872	1109	2265	75	2.71	143.1
1999	4481	1142	2329	73	2.75	147.3
2000	4349	1297	2496	76	2.68	152.7
2001	3954	1345	2857	76	2.97	161.7
2002	4222	1300	2856	75	2.92	168.6
2003	4248	1227	2766	75	2.92	178.7
2004	4487	1252	2803	74	2.91	182.8
2005	4204	1590	3779	87	2.88	186.3
2006	4000	1694	4074	88	3.00	192.7
2007	3785	2121	4801	98	2.84	204.9

Sources: Authors' estimations based on ENIA.

Figure 1. The Evolution of Productivity
(1998=100)



Based on these estimates, we analyze the evolution of productivity dispersion as a measure of labor misallocation in Chilean manufacturing over the years 1990 to 2007. Olley and Pakes (1996), Levinsohn and Petrin (2003), Micco and Pagés (2004), Micco and Repetto (2014) and others have, in different contexts, estimated the potential gains from inputs and outputs reallocation across plants. Hsieh and Klenow (2009), for instance, estimate the extent of misallocation in China and India relative to the United States based on a model of heterogeneous firms and monopolistic competition. According to their estimates, if inputs were reallocated from firms with low to firms with high marginal productivity until productivity dispersion equaled that observed in the US, aggregate total factor productivity would increase by 30%–50% in China and by 40%–60% in India.

In this paper we do not impose the structure of Hsieh and Klenow (2009) to our data. Furthermore, we allow for dynamic sources of dispersion. We do follow their study, however, in relating the dispersion of productivity across plants to labor misallocation. In what follows, we first study the evolution of the distribution of relative productivity over our sample period. We then relate this evolution to changes in the adjustment speed of plants and in the variance of the shocks faced.

IV. The evolution of dispersion

Table 2 displays several points in the distribution of relative productivity for the full sample period. Recall that the number of workers weights plants' productivity so the distribution depicts employees and their productivity within plants. The statistics in the Table confirm the existence of wide differences in productivity across plant employees even within narrowly defined industries. Employees in the first percentile are 65% less productive than the average, whereas employees in the 99th percentile are 552% more productive.[18] Large gaps are still observed at less extreme points of the distribution. For instance, percentile 20 is 30% less productive than the mean, whereas percentile 80 is 79% more productive.[19]

Figure 2 plots the evolution of alternative measures of labor productivity dispersion in our sample of plants without using weights; that is, the standard deviation[20] and the difference between percentiles 99 and 1, between percentiles 90 and 10, and so on. These alternative series are highly correlated; e.g., the simple correlation of the standard deviation and the gap between the 95th and the 5th percentiles is 0.96. Figure 3 also shows that the unweighted standard deviation follows a very similar time pattern than its weighted counterpart.[21]

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[18] Recall that productivity is expressed in natural logarithms, so the first gap reported is calculated as 65%=exp(-1.04)-1.

[19] According to our estimates, the dispersion in Chile lies in between Hsieh and Klenow's estimate of the dispersion in China and in India and the dispersion in the United States. Although these differences may reflect data sampling, they are also consistent with the relative extent of the observed distortions in these economies as reported by the World Bank's Doing Business reports. Note that the authors use revenue TFP as their measure of productivity. Revenue TFP is calculated on the basis of value added using a sector-specific (instead of plant-specific) deflator. See Foster et al. (2008) for a discussion. For the comparison, we estimated the dispersion of this measure of productivity using our data set for Chile. Results are available upon request.

[20] To estimate the standard deviation we excluded the extreme 0.4% of observations from each tail of the distribution.

[21] Weighting the mean to define relative productivities leads also to very similar results when comparing percentiles within the distribution. The estimates are available from the authors upon request.

Table 2. The Distribution of Productivity Gaps

	Deviation from the Mean	
	Natural Logarithm	%
Percentile 1	-1.04	-65%
Percentile 5	-0.75	-53%
Percentile 10	-0.57	-44%
Percentile 20	-0.36	-30%
Percentile 30	-0.21	-19%
Percentile 70	0.36	44%
Percentile 80	0.58	79%
Percentile 90	0.93	153%
Percentile 95	1.26	253%
Percentile 99	1.87	552%

Figure 2. Evolution of Labor Productivity Dispersion

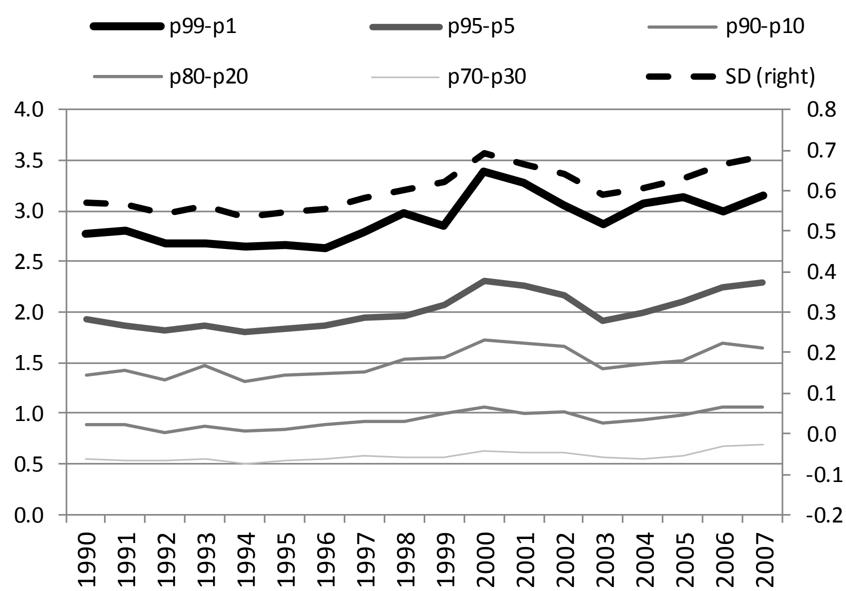
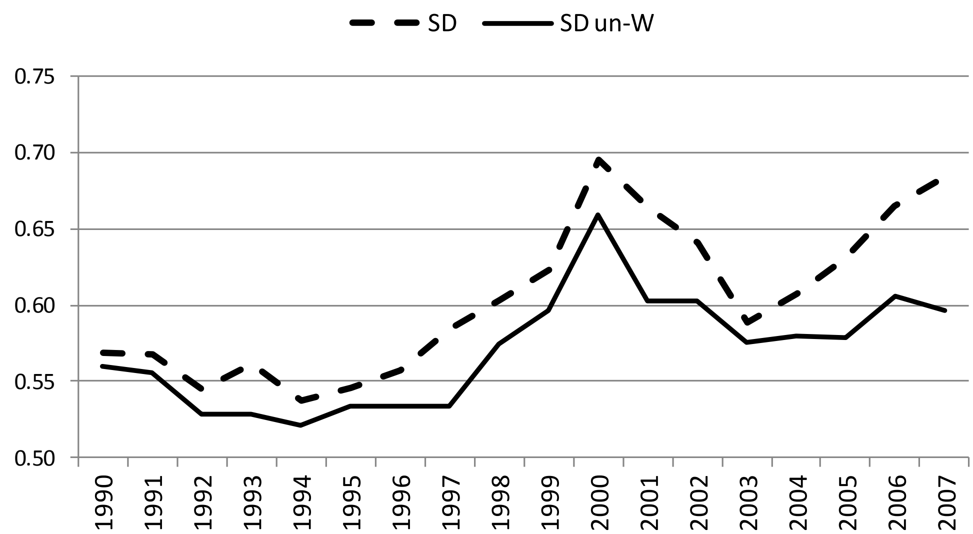


Figure 3. Weighted and Unweighted Productivity Dispersion



As the figures show, dispersion reached its lowest levels in the mid 1990s. The period covering years 1986-1998 has been dubbed by many as the "Chilean miracle" with GDP growth rates reaching annual averages near 7%. Dispersion abruptly increased as the Asian crisis hit Chile and the international markets, coupled with a large increase in the monetary policy interest rate set by the Central Bank. Dispersion, however, declined rapidly: by 2003 it had already returned to a level near its pre-crisis level.

In 2004 our dispersion measures experienced again a relevant rise. By 2007, the weighted standard deviation had risen by 12.5% and the 90th-10th percentiles gap had increased by 10.2%.

Recall that both productivity and its dispersion are a function of the speed of adjustment and the volatility of shocks. In the following sections we estimate the relative importance of these variables. In particular, we are interested in estimating a model in the lines of equation (5) in order to explain the time evolution of productivity dispersion at the industry level.

To estimate this model, however, we need measures of λ at the industry/year level. In what follows we first estimate the speed of adjustment of plants in our data set and its evolution over time. We then identify relevant sources of volatility. With these measures at hand, we proceed to relate the changes in dispersion at the sector level to the volatility of the underlying economic environment and to changes in the measured adjustment speed.

V. Adjustment costs

A growing literature has emphasized the role of microeconomic flexibility in explaining economic growth as it facilitates the Schumpeterian process of creative destruction. In this section, we follow Caballero et al. (2013) in order to estimate how fast Chilean plants adjust their employment levels in the face of shocks.

We estimate the observed changes in employment of plants producing in sector *s* at time *t* as a function of the gap between actual and frictionless employment and a sector-year dummy.[22] The gap is in turn estimated as a function of the difference between the value of labor productivity and the current wage. This procedure allows us to obtain an estimate of the speed of adjustment λ; i.e., the fraction of the employment gap that is closed in the course of a year.

Table 3 reports our results based on two alternative empirical models. The first specification -column (1)- estimates the average speed of adjustment in our data set allowing for heterogeneity across sectors and time; the second model -column (2)- allows for nonlinearities.

[22] See Caballero et al. (2013) for details on the estimation procedure.

Based on the linear model, we find that on average 74% of the employment gap is closed in each period.[23] The estimation results show wide variation in λ across industries and over time. Across sectors, we find estimated interaction terms that vary from 0.194 in sector 314 (tobacco manufactures) to 0.769 in sector 311 (food manufacturing). Over time, our results suggest that the speed at which manufacturing firms adjust in Chile was on average much larger at the end of the sample period than in the early 1990s.

When controlling for the square and the cubic of the employment gap, we find positive estimated coefficients, which in turn imply that plants facing larger gaps adjust more quickly. Both models explain about 50% of the variance in log employment growth.

VI. Uncertainty in the operating environment

We now turn to analyze the factors behind volatility. In this section we identify a number of developments occurring in Chile over the sample years that may have changed the uncertainty firms face. One of these developments has to do with the surge in real interest rates as a response to the Asian currency crisis. Others have to do with changes in the conduct of monetary policy and thus with the volatility of the real exchange rate. Finally, a third set of variables relate to developments in the energy market. Table 4 reports the evolution of the 90-365 days real interest rate, the oil price, the nominal exchange rate and the CPI, along with their standard deviation.

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[23] This average is estimated on the basis of a regression of log employment growth on the employment gap and a constant. We obtain an estimated λ coefficient equal to 0.74 and a standard error equal to 0.009. In a sample of 60 countries, Caballero et al. (2013) find an average estimated λ coefficient equal to 0.6.

Table 3. Speed of Adjustment Estimation Results

	(1) Change in Ln Employment				(2) Change in Ln Employment		
Gap^2		Gap * Isic 311	0.769	Gap^2	0.023	Gap * Isic 311	0.708
			[0.016]**		[0.021]		[0.016]**
Gap^3		Gap * Isic 312	0.656	Gap^3	0.385	Gap * Isic 312	0.592
			[0.038]**		[0.055]**		[0.040]**
Gap * 1991	0.014	Gap * Isic 313	0.685	Gap * 1991	0.014	Gap * Isic 313	0.616
	[0.020]		[0.040]**		[0.020]		[0.040]**
Gap * 1992	0.014	Gap * Isic 314	0.194	Gap * 1992	0.016	Gap * Isic 314	0.049
	[0.023]		[0.418]		[0.023]		[0.479]
Gap * 1993	-0.007	Gap * Isic 321	0.657	Gap * 1993	0.002	Gap * Isic 321	0.605
	[0.019]		[0.024]**		[0.019]		[0.024]**
Gap * 1994	0.02	Gap * Isic 322	0.682	Gap * 1994	0.032	Gap * Isic 322	0.627
	[0.023]		[0.024]**		[0.024]		[0.025]**
Gap * 1995	0.043	Gap * Isic 323	0.663	Gap * 1995	0.048	Gap * Isic 323	0.61
	[0.025]		[0.051]**		[0.024]*		[0.050]**
Gap * 1996	0.106	Gap * Isic 324	0.734	Gap * 1996	0.109	Gap * Isic 324	0.67
	[0.023]**		[0.027]**		[0.023]**		[0.029]**
Gap * 1997	0.036	Gap * Isic 331	0.69	Gap * 1997	0.034	Gap * Isic 331	0.626
	[0.026]		[0.026]**		[0.025]		[0.027]**
Gap * 1998	0.001	Gap * Isic 332	0.604	Gap * 1998	-0.001	Gap * Isic 332	0.539
	[0.023]		[0.036]**		[0.023]		[0.037]**
Gap * 1999	0.049	Gap * Isic 341	0.6	Gap * 1999	0.04	Gap * Isic 341	0.548
	[0.026]		[0.047]**		[0.025]		[0.047]**
Gap * 2000	0.099	Gap * Isic 342	0.718	Gap * 2000	0.098	Gap * Isic 342	0.667
	[0.024]**		[0.039]**		[0.024]**		[0.039]**
Gap * 2001	0.117	Gap * Isic 351	0.464	Gap * 2001	0.1	Gap * Isic 351	0.395
	[0.033]**		[0.049]**		[0.031]**		[0.049]**
Gap * 2002	0.033	Gap * Isic 352	0.67	Gap * 2002	0.03	Gap * Isic 352	0.615
	[0.026]		[0.030]**		[0.026]		[0.030]**
Gap * 2003	0.109	Gap * Isic 354	0.608	Gap * 2003	0.121	Gap * Isic 354	0.53
	[0.028]**		[0.071]**		[0.028]**		[0.070]**
Gap * 2004	0.04	Gap * Isic 355	0.665	Gap * 2004	0.035	Gap * Isic 355	0.603
	[0.022]		[0.041]**		[0.022]		[0.040]**
Gap * 2005	0.12	Gap * Isic 356	0.7	Gap * 2005	0.107	Gap * Isic 356	0.643
	[0.032]**		[0.026]**		[0.032]**		[0.027]**
Gap * 2006	0.159	Gap * Isic 361	0.452	Gap * 2006	0.146	Gap * Isic 361	0.405
	[0.033]**		[0.085]**		[0.032]**		[0.085]**
Gap * 2007	0.144	Gap * Isic 362	0.653	Gap * 2007	0.134	Gap * Isic 362	0.599
	[0.031]**		[0.080]**		[0.031]**		[0.078]**
		Gap * Isic 369	0.674			Gap * Isic 369	0.604
			[0.024]**				[0.026]**
		Gap * Isic 371	0.53			Gap * Isic 371	0.474
			[0.043]**				[0.045]**
		Gap * Isic 372	0.449			Gap * Isic 372	0.406
			[0.046]**				[0.046]**
		Gap * Isic 381	0.631			Gap * Isic 381	0.568
			[0.020]**				[0.021]**
		Gap * Isic 382	0.591			Gap * Isic 382	0.53
			[0.025]**				[0.026]**
		Gap * Isic 383	0.609			Gap * Isic 383	0.562
			[0.034]**				[0.033]**
		Gap * Isic 384	0.552			Gap * Isic 384	0.489
			[0.027]**				[0.028]**
		Gap * Isic 385	0.688			Gap * Isic 385	0.643
			[0.114]**				[0.113]**
Observations		60389				60389	
R-squared		0.49				0.5	
Sector Year fixed effects		YES				YES	

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

Interest Rate Hikes

Firms in Chile mainly rely on banks for finance, especially small firms that have no access to the equity market or the domestic corporate bond market (Caballero 2000). So large interest rate fluctuations, as the one observed in 1998, leave firms with little access to funding sources (Table 4). This in turn limits the ability of the economy to efficiently reallocate resources and to smooth shocks when needed.

Table 4. Interest Rate, Exchange Rate and Oil Price Evolution

Year	Real Interest Rate [%]	Oil Price Brent $/bbl	Nominal Exchange rate $/US$	Consumer Price Index	Real Interest Rate StdDev/Mean	Oil Price Brent StdDev/Mean	Nominal Exchange rate StdDev/Mean
1990	13.28	7232.32	304.90	42.71	2.1523	0.3628	0.0444
1991	8.48	6987.44	349.21	52.02	0.4825	0.0892	0.0326
1992	8.13	7006.50	362.58	60.04	0.3830	0.0723	0.0364
1993	9.23	6858.29	404.17	67.69	0.1809	0.0768	0.0276
1994	9.27	6623.35	420.18	75.43	0.2725	0.0723	0.0201
1995	8.53	6770.42	396.77	81.64	0.3634	0.0588	0.0370
1996	9.34	8534.09	412.27	87.65	0.1986	0.1090	0.0116
1997	8.77	8030.48	419.31	93.03	0.2379	0.0894	0.0165
1998	11.93	5873.20	460.29	97.78	2.6124	0.1013	0.0181
1999	8.19	9160.24	508.78	101.04	0.9238	0.3305	0.0466
2000	7.48	15368.80	539.49	104.93	0.2491	0.1421	0.0494
2001	6.33	15419.81	634.94	108.67	0.7586	0.1077	0.0790
2002	4.39	17264.57	688.94	111.38	1.6583	0.1438	0.0421
2003	4.30	20033.48	691.40	114.51	1.1565	0.1165	0.0654
2004	3.17	23346.66	609.53	115.71	1.1747	0.1623	0.0394
2005	3.95	30367.01	559.77	119.25	1.2918	0.0974	0.0452
2006	5.18	34554.81	530.28	123.29	1.2438	0.0916	0.0153
2007	4.64	37767.87	522.47	128.72	0.9034	0.1417	0.0280

Source: Real interest rate (90 days-1 year), CPI and Exchange rate: Central Bank. Oil price: Platt´s, OLADE.

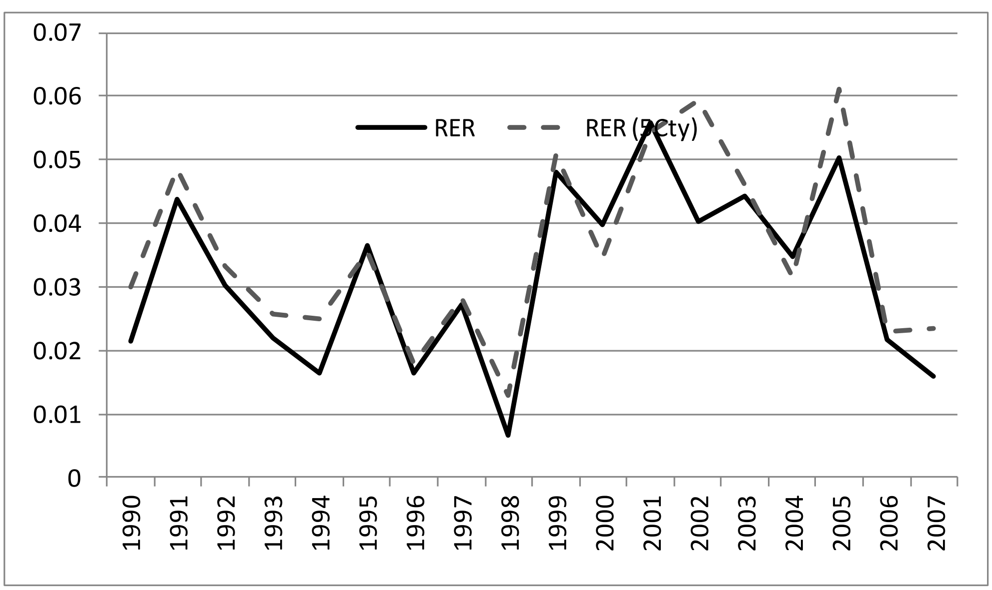
Note: Nominal exchange rate and oil price are in natural logs divided by the year average CPI.

Real Exchange Volatility

Another potential factor affecting observed volatility in the labor market is the monetary policy adopted by the Central Bank since 1998. Inflation targeting targets nominal inflation at a two-year horizon at the expense of not targeting nominal or real exchange rates. Figure 4 shows the evolution of the observed real exchange volatility measured within years. Two indices are constructed: RER is the rate relative to all of Chile’s commercial partners, whereas RER(5Cty) considers the five most relevant ones only.

During the period 1990 and 1997, the average real exchange rate volatility, measured by the monthly standard deviation, equaled 2.7%. This measured mean volatility jumped sharply to an average of 3.9% during the period 1999-2007. Real exchange rate volatility affects both demand and total costs. This higher volatility requires more labor adjustment and therefore, under the presence of adjustment costs, leads to higher labor productivity dispersion.

Figure 4. Real Exchange Rate Volatility

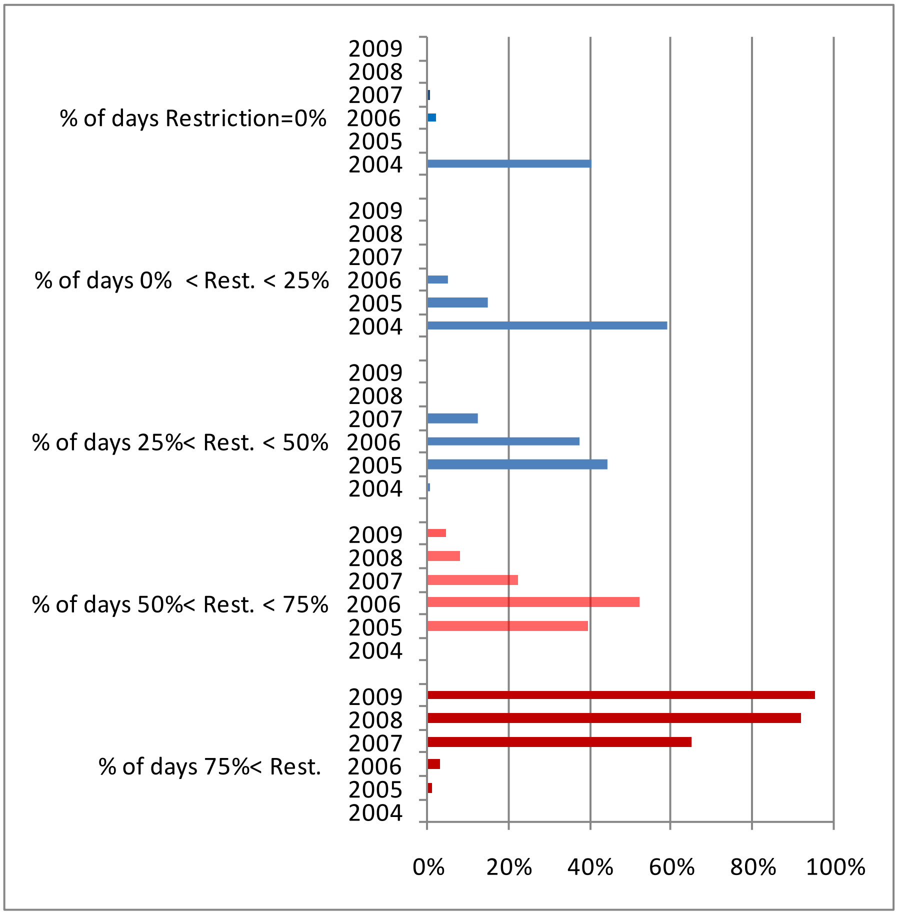


Energy Prices

Since the 1990s, Chile invested in natural gas power plants and in cross-border pipelines in order to import energy from Argentina. The economy also invested in the conversion of industries and homes to the use of natural gas. In April 2004, however, in response to a local energy shortage, the Argentinean authorities cut natural gas exports to Chile. Production had to switch to diesel and old coal powered plants had to be brought back to service. Since then, gas supply has been erratic. Figure 5 reports the fraction of days that gas imports have been restricted classified according to the fraction of contracted supply that was not delivered. The Figure also shows how supply cuts have become more frequent over time.

These developments led many firms to switch to oil. During this period, oil prices were also characterized by a higher level of volatility. Oil price volatility within a year –measured by its standard deviation- increased from an average of 9.9% during years 1996 and 1997 to an average of 14.4% during the period 1998-2007 (Table 4). Plants have different energy requirements; thus this increasing uncertainty in energy prices mainly affects the most energy intensive plants.

Figure 5. Restrictions on Imports of Argentinean Natural Gas



VII. Volatility, adjustment costs and the evolution of dispersion

In this section we provide a very simple test of our main hypothesis by estimating the relationship between the observed dispersion of productivity, economic shocks, and the adjustment speed of firms. More specifically, this simple model relates the standard deviation of the natural log of our productivity measure at the sector/year level to the estimated adjustment speed and to variables proxying for shocks as described above --the volatility of the exchange rate, of the interest rate and of the price of oil, as well as the fraction of days in a given year firms experienced gas cuts--.

Our basic model can be summarized as follows

$$Y_{st} = \lambda_{st}\delta_0 + \mathrm{var}(A_{st})\delta_1 + \mathrm{var}(A_t)d_{As}\delta_2 + X_{st}\theta + \alpha_s + \alpha_t t + \varepsilon_{st}$$

where Y_{st} denotes our measure of productivity dispersion in sector s and year t, λ_{st} is the estimated adjustment speed of firms producing in sector s/year t, $var(A_t)$ is a measure of volatility in year t, and d_{As} is a dummy variable indicating whether A is a relevant profit shifter for sector s. The model also includes sector fixed effects α_s and a time trend, and exogenous controls summarized in vector X.[24]

Our empirical analysis allows for a number of variables capturing the volatility of the profit shifter A. Thus the vector of dummy variables d_A describes whether the sector is relatively open to international trade, capital intensive, oil intensive and gas intensive. These sectorial characteristics are then interacted with the relevant variables proxying for each type of shock; i.e., the volatility of the real exchange rate, of the real interest rate, and of the oil price, and the measure of natural gas shortages.

We define a sector as open if, according to the input-output matrix of 1996, the sum of exports and imports over total supply (domestic output plus imports) is higher than the median. Similarly, a sector is defined as capital intensive if the average ratio --across plants and years in the ENIA-- of value added minus the wage bill over gross output is higher than the median. Oil intensity is in turn defined on the basis of the value of oil expenses over gross output, whereas gas intensity is measured on the basis of energy expenses different from electricity and oil over gross output. Finally, the variable “gas cuts” measures the percent of gas that was not delivered compared to the contracted level as the benchmark, averaged across days.

[24] We also estimate this model using year fixed effects instead of a time trend. The vector X contains the within year average of the real exchange rate, the real interest rate and the price of oil.

We also extend this model to allow for interactions with the adjustment speed of plants at the sector/year level. That is, we also estimate the following model

$$Y_{st} = \lambda_{st}\delta_0 + \text{var}(A_{st})\delta_1 + \text{var}(A_t)d_{As}\delta_2 + \text{var}(A_{st})d_{As}\lambda_{st}\delta_3 + X_{st}\theta + \alpha_s + \alpha_t t + \varepsilon_{st}$$

It is worth emphasizing that our models do not explicitly include measures of *var(τ)*. Given that cross-industry measures of regulations and exemptions are not available, we assume that *var(τ)* can be captured by the fixed effects and the error term. That is, the error term captures both measurement error and unobserved variation in static distortions across industry and over time. We assume that this unobserved variability is not related to either the costs of adjustment or the volatility of the operating environment. If this is not true, then our estimates will be biased. To the best of our knowledge, during 1990-2007 there have been no regulatory changes that could have affected plants in different ways.

The estimation results are reported in Table 5. The first column relates the observed dispersion in labor productivity to the volatility of shocks. According to our estimates, a rise in the dispersion of the exchange rate does not affect significantly the dispersion of labor productivity unless the sector is classified as open. Our point estimate indicates an effect equal to 20% of one standard deviation of labor productivity dispersion when the exchange rate dispersion increases by one standard deviation (keeping its average constant).

Similarly, a rise in the dispersion of the real interest rate leads to a statistically significant rise in the dispersion of productivity as long as the sector uses capital intensively. The effect is relevant and amounts to a rise of 19% of one standard deviation of labor productivity dispersion in capital- intensive sectors whenever the dispersion of the interest rate rises in one standard deviation (again, keeping constant the average interest rate).

Moreover, we find that oil price dispersion is correlated with a lower standard deviation of labor productivity, unless the sector uses oil intensively. The net effect on oil intensive sectors, though, is not statistically significant. We find a similar result for the effect of gas cuts: more frequent natural gas restrictions reduce the dispersion of labor productivity, unless the sector uses natural gas intensively. Again, the net effect on gas intensive sectors is not statistically significant.

Column (2) replaces the time trend for year dummies. In this case we find very similar results: when the volatility of shocks to the operating environment rises, the labor productivity dispersion of the relevant sectors also rises. The estimated coefficients are of similar magnitude as in column (1) and are all statistically significant.

Column (3) replicates the model in column (1), but this time we add the estimated speed of adjustment at the sector/year level. Given that our measure of λ is an estimate of its true value, we report bootstrapped standard errors.

We find a negative and significant effect of λ on labor productivity dispersion. That is, whenever firms are able to adjust more quickly, the dispersion of productivity is reduced. This effect is also economically large. Were the adjustment speed to increase from percentile 25^{th} (manufacturing of other non-metallic mineral products and of electrical machinery, sectors 369 and 383 respectively) to that of percentile 75^{th} (beverage industries and wood products other than furniture, sectors 313 and 331, respectively), then labor productivity dispersion would fall by almost half of one standard deviation. The remainder of the results are qualitatively the same; that is, the volatility of shocks has a positive effect on the dispersion of labor productivity whenever the shock proxies a profit shifter that is relevant for the industry.

Finally, column (4) adds interactions of λ with the relevant shocks at the sector level. Although none of these interaction terms turn out to be statistically significant, our previous results remain unchanged.

Summing up, the results of this very simple econometric exercise are consistent with the hypothesis that labor productivity dispersion is related to the variance of shocks and the speed at which firms adjust. The effects are both large and economically relevant.

Table 5.The Dispersion of Labor Productivity, Adjustment Speed, and the Volatility of Shocks

	(1)	(2)	(3)	(4)
λ (estimated adj. speed)			-0.716***	-0.789***
			[0.248]	[0.395]
SD exchange rate	-0.435		0.0282	0.0742
	[0.938]		[0.456]	[0.548]
Open sector x SD exch rate	2.586**	2.613**	2.300***	3.452***
	[1.084]	[1.060]	[0.192]	[1.676]
λ x Open sector x SD exch rate				-1.993
				[2.834]
SD interest rate	-0.012		-0.0430***	-0.0431*
	[0.0135]		[0.00799]	[0.0230]
Capital intensive sector x SD int rate	0.0487**	0.0487**	0.0664***	0.0375
	[0.0198]	[0.0195]	[0.0153]	[0.0981]
λ x Cap intesive x SD interest rate				0.0611
				[0.124]
SD oil price	-0.241**		-0.280***	-0.287*
	[0.117]		[0.0481]	[0.156]
Oil intensive sector x SD oil price	0.233*	0.233*	0.538***	-0.454
	[0.130]	[0.130]	[0.185]	[1.010]
λ x Oil intensive x SD oil price				1.611
				[1.675]
Gas cuts (%)	-0.131**		-0.220***	-0.222***
	[0.0570]		[0.0163]	[0.0295]
Gas intensive sector x Gas cuts (%)	0.142**	0.141***	0.133**	0.216
	[0.0555]	[0.0541]	[0.0584]	[0.356]
λ x Gas intensive x Gas cuts				-0.131
				[0.510]
Year	0.00442		0.0167***	0.0168***
	[0.00496]		[0.000156]	[0.00244]
Observations	484	484	457	457
R-squared	0.519	0.547	0.548	0.551
Sector fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	No	Yes	No	No

*** p<0.01, ** p<0.05, * p<0.1.

Standard errors in brackets. Robust standard errors in models (1) and (2). Bootstrapped standard errors in models (3) and (4).

All models include the within year average exchange rate, interest rate and oil price.

VII. Conclusion

In this paper we analyze the evolution of labor productivity dispersion in Chile. Following Hsieh and Klenow (2009) we claim that labor productivity dispersion leads to lower aggregate productivity. However, their static analysis assumes that dispersion is a result of static distortions that allow some firms to survive over time despite displaying relatively low factor productivity. We extend their analysis by hypothesizing that labor adjustment costs also generate gaps between nominal labor productivity and wages in the presence of shocks. Thus the observed dispersion may be the result of both static and dynamic distortions.

To study the importance of adjustment costs and volatility in labor productivity dispersion we analyze manufacturing firms' labor productivity in Chile over the 1990 and 2007 period, by relating its dispersion to the operating environment uncertainty and adjustment costs. Our econometric models do find a relevant role for both, the volatility of the shocks firms face and the speed at which they adjust when hit by these shocks.

In this paper we associate volatility to macroeconomic developments such as changes in the conduct of monetary policy and the exchange rate, and energy shocks. These shocks are exogenous to the individual plants in our data set, and hence allow us to identify exogenous changes in the volatility of the economic environment. Future work may more directly identify the dynamic process of productivity and profitability that firms face.

In addition, with these idiosyncratic dynamic processes at hand, future work could also analyze the differential effect on dispersion of transitory versus permanent shocks, and from positive versus negative shocks.

Finally, future work might also be better able to identify changes in static distortions. This would allow for a better measurement of the welfare gains from removing such distortions.

Acknowledgements

We thank Ricardo Caballero, Vittorio Corbo and seminar participants at CEP for helpful comments and suggestions. We are also grateful to Pablo Muñoz for excellent research assistance. This paper is part of a project on labor market adjustments funded by Fondo Nacional de Desarrollo Científico y Tecnológico (Fondecyt Project 1120869).

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