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The Impact of Extended Employment Protection Laws on the Demand for Temporary Agency Workers

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Abstract

The incidence of alternative work arrangements has risen during recent decades, affecting the shape of the economy and leading to calls for changes in labor regulation. In this paper, we study the demand for temporary agency work (TAW) and the effects of a reform in Chile that increased the regulatory burden on TAW. In examining a sample of manufacturing plants, we not only show that plant-level volatility and relative size are key determinants of the demand for TAW, but also that both characteristics became more important after the change in regulation. We also evaluate the effects of the regulation on the plants' performance. We find that plants using TAW increased their share of non-agency workers by around 12%, while their total employment shrank by 7% as a response to the regulation. Reassuringly, plants with higher shares of agency workers—consequently more exposed to the regulatory change—experienced larger changes in employment. Finally, we only find partial evidence of a differential negative effect on output, and we do not detect any significant impact of this regulation on value added.

Key Words: employment composition, employment protection and demand for temporary agency workers.

JEL Classification: J41, J08.

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1. Introduction

Labor markets are moving beyond standard work arrangements, blurring the boundaries of employment relationships. One of the most rapidly growing forms of alternative work arrangements is the use of temporary agency workers, also known as temporary help jobs.[1] Agency work involves a specific type of contractual relationship: workers are hired by an agency and temporarily assigned to perform work at a user firm, creating a triangular connection between the worker, the temporary agency, and the firm. The rapid spread of temporary agency work (TAW) has led to calls for new regulations in many countries, especially in Europe (e.g. Temporary Agency Work Directive 2008/104/EC). Despite the growth of TAW and policy interest in agency workers' conditions, research on the effects of its regulation is—to the best of our knowledge—nonexistent.

Most of the existing literature on TAW has attempted to explain why firms use these temporary workers. The leading explanations include: (1) agency workers can provide a flexible buffer for times of uncertainty or for demand fluctuations (Houseman, 2001; Houseman et al., 2003; Jahn and Bentzen, 2010; Hirsch and Mueller, 2012); (2) firms might use agency employment to circumvent regulations that make labor adjustments costly (Bauman et al., 2008; Boeri, 2011, Autor, 2013);[2] and (3) temporary work agencies could help user firms screen workers (Autor, 2001). On the supply side, only a few papers have looked at how these newly formed labor relationships affect workers, mostly arriving at inconclusive results. While some authors argue that TAW is a stepping-stone into stable and regular employment (i.e. Ichino et al., 2006; Jahn and Rosholm, 2012), others find that agency workers have less access to training and face a higher risk of unemployment (Nienhüser and Matiaske, 2006; Autor and Houseman, 2010).

Like most countries, Chile has experienced a rapid expansion in the number of agency workers. In the manufacturing sector, the share of TAW almost doubled within a span of 6 years, from 7% in 2001 to more than 12% in 2006. Concerns over this expansion, and the perceived

[1] See, for instance: Neugart and Storrie (2008), Houseman (2014) and Katz and Krueger (2017).

[2] This motivation could be accentuated in more rigid and/or more volatile labor markets, a feature that we explored with a theoretical model in an earlier version of this paper. The model is available upon request.

precariousness of temporary work, led to the enactment of a new law in 2007. This law—called *"Ley de Subcontratación"* (Ley 20.123)—regulated TAW for the first time, making beneficiary user firms accountable for the legal rights of the workers hired through an agency, consequently increasing the cost of using agency workers. As a result, the share of TAW started to decrease immediately after this law was enacted, reaching a plateau of around 10% by 2010.

This paper not only provides novel evidence on the effects that TAW regulation had on plant performance; it also contributes to the existing literature on plant characteristics and the demand for TAW. Previously, data unavailability has posed a fundamental problem for the study of how plant characteristics affect the use of agency workers. In Chile, the National Institute of Statistics began recording information on agency workers in 2001 after realizing how important TAW use was for many manufacturing firms.[3] This feature, together with early regulation of agency employment, make the Chilean experience an appealing case of study. Finally, it is worth noting that we analyze the use of agency employees who perform jobs equivalent to those performed by regular workers; accordingly, we do not study wholly outsourced functions—such as cleaning, food services, or security tasks— which have been the focus of recent research (e.g. Goldschmidt and Schmieder, 2017).

We start by studying the role plant volatility plays on the demand for agency employment. The main challenge for identification is reverse causality. On one hand, firms that need more flexibility use more agency workers. On the other hand, the use of agency workers provides flexibility for the plants.[4] Thus, in order to correctly measure plant volatility, one needs to deal with the positive bias from endogeneity. For this, we exploit variation of the exchange rate and the energy prices of oil and electricity. Specifically, we regress the log change of nominal value-added on (1) the exchange rate movement times the plant export share (export to nominal output ratio), (2) the exchange rate movement times the plant import share (imported inputs to nominal output ratio), and (3) the oil and electricity price movements times the oil and

[3] Workers from the National Institute of Statistics, responsible for the manufacturing survey used in this paper, commented to us that they included questions on TAW because they noticed that the invisibilization of this type of employment might significantly bias measures of capital per worker and labor productivity.

[4] In Chile, agency workers have lower adjustment costs than regular workers. By Law, if a firm dismissed a permanent worker, then the worker has the right to claim a severance payment of one monthly wage per year of work, up to the eleven years (See Heckman and Pages (2003) for more details). However, before the regulation, the user firms were not responsible for the severance payments of agency workers.

electricity plant shares (oil and electricity expenditure to nominal output ratios). Using this "price-trough" specification, we estimate the response of value added to "exogenous" price variation, which we can use to construct a "clean" measure of volatility. Following Ramey and Ramey (1995), we define volatility as a 5-year moving average of the standard deviation of the predicted log change in value added. We also study how plant size impacts the demand for TAW. In an attempt to avoid spurious correlations between the current number of agency workers hired and plant size (total employment), we use the panel structure of our data to define size as the fourth lag of total employment.

We find that plant volatility is strongly associated with the use of TAW, especially at the intensive margin. A one standard deviation rise in plant volatility (0.02) implies a 0.014 increase in the share of TAW. This is an economically significant impact if we consider that the unconditional simple average share of TAW in our sample is 0.037, and the simple average share of TAW conditional on positive TAW employment is 0.205. Interestingly, the association between volatility and TAW became stronger after the regulation, suggesting that during the pre-reform period, plants were using agency workers for reasons other than to cope with volatility (i.e., regulatory arbitrage or screening of workers).

Furthermore, we identify plant size as another important characteristic linked to the use of agency workers. A one standard deviation increase of size (1.11) implies a 0.11 increase in the share of TAW. We interpret this result as an indication of the existence of fixed costs associated with the use of agency workers (e.g., the cost of administrating contracts between user firms and work agencies). Consistent with our interpretation—and with the increase in the costs of using TAW triggered by the reform—we find that the link between size and TAW intensifies after the reform.

How do employers react to an increase in the cost of TAW? To answer this question, we exploit the variation generated by the change in the regulation on TAW in 2007. Comparisons of employment, output, and other measures of plant performance at plants using TAW and plants not using TAW (as of 2006) before and after the increase in the cost of TAW offer a simple method for evaluating the effects of this regulatory change. Comparisons accounting for variation between initially high users of TAW (i.e. plants with a TAW share above the median as of 2006) and other TAW users provide an alternative estimate of the impact of the TAW regulation on plant performance.[5]

Results from our main empirical specifications capture differences between TAW users and non-users, both before and after the regulation; and differences in the intensity of use of TAW (%TAW), which arguably reflects the degree of exposure to the TAW regulation. Reassuringly, both approaches lead to similar conclusions. After accounting for time fixed effects, plant specific unobservables, and TAW-user specific trends, as well as controlling by variation in several input prices, we find robust evidence of substitution and scale effects of the regulation on employment.

After the regulation, plants that were using agency workers substituted towards regular employees. The share of non-agency workers decreased by 12.5% (from an average of 80% among TAW-user plants), and the absolute number of non-agency employees increased by 9%. Despite this substitution towards regular contracts, total employment shrank by 7% in TAW-user plants.

Evidence on the effects of this regulation on other measures of plant performance is also consistent with scale and substitution effects. We find that output decreased by 6% in TAW-user plants and the share of inventories over output increased by 2 percentage points (from a base of 20%). While the former is consistent with the negative income effect on total employment, the latter could be interpreted as a substitution response because inventories, as well as agency workers, could be used to cope with volatility (Christiano, 1988). Finally, we do not find any effect of this reform on value added.

An issue with interpreting these estimates is that using agency work is a decision made by the firms. Consequently, TAW-users might be intrinsically different from non-users. We explore the extent to which the estimated effects could be confounded by such pre-determined differences between TAW-user and TAW-nonuser plants by implementing an event study. We conclude that there are no significant differences between TAW-user and TAW-nonuser plants

[5] This approach is similar to the one presented in Card and Krueger (1994).

in terms of value added, non-agency employment, and inventories share. However, total employment and output were growing in TAW-user plants, depicting a pattern similar to an Ashenfelter's dip reflection. From this, it seems to follow that the effects of the reform along these dimensions could be underestimated, a problem that we tried to ameliorate by including TAW-user-specific trends in the main specifications described above. Finally, as expected from the previous findings, the share of non-agency employment was decreasing in TAW-user plants before the reform, but it increased afterwards.[6]

To clear further identification concerns, in the last section of the paper we perform several robustness checks: (1) We estimate exposure effects on a sample of TAW-user plants; (2) we improve our control for pre-trends by estimating a model with lagged dependent variable and plant fixed effects (Angrist and Pischke, 2008), as well as a model with plant fixed effects and plant-specific time trends; and (3) we implement a control function approach (Heckman, 1979) to account for plants' unobservable characteristics that are associated with the decision to use agency workers.[7]

Pooling all these specification checks, we find a negative effect on total employment and output, with estimates ranging from -9% to -6%, and from -14% to -3%, respectively. We also estimate a positive effect in the share of non-agency workers, within a range of 6% to 10%, which comes from both a decrease in the share of TAW and an increase in the use of non-agency workers. These results also confirm that there was no effect on value added. However, these specifications falsify (at standard risk levels) the hypothesis that plants can substitute agency workers with inventories as a strategy to deal with volatility.

The paper proceeds as follows. In Section 2, we present the reader with the institutional background of the TAW regulation and show preliminary evidence using aggregate data. Section 3 describes the data used in the analysis and also presents some informative correlations. Section 4 contains the empirical analysis, which is divided in two parts: Section

[6] This is a direct consequence of the increase in the share of agency workers, because the levels of non-agency employment were the same among users and non-users of TAW before the reform.

[7] Following Kline and Walters (2017) we also complement this approach with two-stage least squares estimation.

4.1 shows the determinants in the demand for TAW, and section 4.2 presents the main estimates of the regulation's effects on plants' performance. We complement section 4.2 with a series of robustness checks presented in section 5. Finally, Section 6 concludes.

2. TAW regulation and Aggregate Effects

Chile experienced large expansion in the number of agency workers at the turn of the twenty-first century. As a response, unions and politicians raised concerns about the impact of this new type of employment on worker welfare. Public discussion catalyzed into new regulation for non-standard work arrangements. The aim of the Chilean regulation on agency work employment, created in October 2006 and enforced since January 2007, was to level working conditions between agency and regular workers and to enforce temporary agency workers' labor rights, in the same spirit of regulation in Europe.[8] Specifically, the Chilean reform incorporated the following changes to the Labor Code:

- The user firms became accountable for the labor rights of agency workers, including severance payments. The new Law stated that in the case of a violation of the Labor Code, agency workers can sue either their agency or the user firm in which they work.
- User firms can request information from temporary-work agencies regarding compliance with the labor rights of their agency workers. If the agencies do not prove that they are compliant with Labor Code obligations in a timely manner, then the user firms can withhold the appropriate amount from the agency fee to meet agency worker labor rights. In this case, agency workers can only sue the user firm after the prosecution of the agency has been exhausted.
- Finally, user firms take on the responsibility of protecting the lives and health of all workers in their workplaces, regardless of their employment contract.

[8] For instance, the main goal of the DIRECTIVE 2008/104/EC of the European commission on temporary agency work is to ensure that *"the basic working and employment conditions applicable to temporary agency workers should be at least those which would apply to such workers if they were recruited by the user undertaking to occupy the same job".*

Prior to this Law, temporary work was completely unregulated; and labor regulation for other types of employment did not change in the time we study. Only one other reform—called *"Nueva Justicia Laboral"*— was enacted during this period (in 2009), but it does not affect our empirical approach. This reform changed the procedures to solve labor controversies from written to oral trials and increased the number of labor courts from twenty to eighty-four in order to improve the enforceability of labor regulations. However, this reform made no distinction between permanent and agency workers, and therefore it should not confound the effects of the TAW regulation.[9]

The effects of the TAW regulation show up right away in aggregate data on Chilean manufacturing. Figure 1 below plots the share of agency workers involved in the production process in this sector by year. We observe that the share of TAW went from 7% in 2001 to almost 13% in 2006. After the TAW regulation, this positive trend broke, and the share of TAW started to fall. By 2011, TAW represented only 10% of total employment.

[FIGURE 1 HERE]

To zoom in on this aggregate dynamic, we perform an accounting exercise that decomposes the aggregate evolution of the TAW share around the time of the regulation, as follows:

$$Share\ of\ TAW = \frac{\sum_{i\in U} TAW_i}{\sum_{i\in U}(TAW_i + R_i) + \sum_{i\notin U} R_i}$$

$$= \underbrace{\frac{\sum_{i\in U} TAW_i}{\sum_{i\in U}(TAW_i + R_i)}}_{\substack{Weighted\ Avg.\ of \\ TAW\ Share\ \text{in TAW−users}}} \times \underbrace{\frac{\frac{\sum_{i\in U}(TAW_i + R_i)}{N_U}}{\frac{\sum_{i\in U}(TAW_i + R_i) + \sum_{i\notin U} R_i}{N_U + N_{-U}}}}_{Rel.\ Size\ of\ TAW-user\ Plants} \times \underbrace{\frac{N_U}{N_U + N_{-U}}}_{Share\ of\ \text{TAW−user}\ Plants}$$

Eq. [1]

Where TAW_i reflects the number of temporary agency workers and R_i the number of regular

[9] See Rosado Marzán (2009) for a discussion about labor regulation in Chile during this period.

workers in plant i. U identifies TAW-user plants, and the terms N_U and N_{-U} denote the number of TAW-user plants (plant with $TAW_i > 0$) and the number of plants without any agency worker ($TAW_i = 0$). Equation [1] decomposes the share of TAW in manufacturing (weighted average of TAW share in all plants) into three components: first, the weighted average of TAW shares in users´ plants (TAW>0); second, the size of TWA-user plants relative to all plants in manufacturing; and third, the share of TAW-user plants. Figure 2 shows the evolution of each of these components over time.

[FIGURE 2 HERE]

This figure highlights the evolution of both the extensive (share of TAW-user plants) and intensive margins (TAW share and relative size of TAW-user plants) of TAW use. On one hand, the TAW regulation is correlated with a decrease in the share of plants using agency workers and with an increase in the relative size of those plants. On the other hand, in plants using TAW, the weighted and unweighted shares of TAW decreased after 2006. The fact that the amplitude of the pre-post reform change is larger for the weighted average indicates that there was an increasing correlation between plant size and the share of TAW prior to the reform. Remarkably, there was a reversal of this correlation after the reform. In Appendix A we show an alternative decomposition of the aggregate share of TAW that accounts for this correlation. Finally, Figure 2 also suggests that the TAW regulation increased both the relative cost of agency workers *vis-à-vis* regular workers (fall in the intensive margin) and the fixed cost of having agency workers (fall in the number of plants using TAW and increase in the relative size of plants using them). Section 4.1 explores these features of the data in more depth.

3. Data

Our data on agency workers comes from the Chilean Annual Manufacturers Survey (ENIA). The ENIA is an unbalanced panel of annual data. It covers all manufacturing plants with 10 or more employees and represents approximately 50% of total manufacturing employment in Chile. The survey started in 1979, but information on agency workers has only been recorded since 2001. Among the plant’s characteristics, we observe: the number of employees (divided into regular and agency workers), the value of raw materials, energy consumption, sales, exports, imports, output, and value added. We also have the industry classification codes and the value of the physical inventory at the beginning and end of the year. Using data from 1995, we also construct a proxy for plant volatility as the standard deviation of five lags of the log change in value added. Appendix B presents more details about this dataset, the variable definitions, and descriptive statistics.

It is worth highlighting that the employment data on agency workers refers to employees who perform jobs equivalent to those performed by regular workers; accordingly, we do not study wholly outsourced functions such as cleaning, food services, or security tasks. This distinction is important since it allows us to focus on workers who are close substitutes to each other, not complements who might conduct different tasks within the firm, as in Goldschmidt and Schmieder (2017).

Table 1 presents the number of observations, the sample mean, and the standard deviation of the main variables used in our analysis: total employment, TAW share, log output, log value added, and the ratio between the value of inventories and the value of output. We divide the sample into four groups: plants with and without any TAW, before and after the reform (2007). For the period before the legal change, we have 30.067 plant-year observations, from which 18.7% (5.992 obs.) are plant-years with at least one TAW. This figure is 16.3% for the second period. On average, the share of plants with at least one TAW fall by 2.4 percentage points after the labor reform.

During the post-reform period, the average plant with at least one TAW became larger relative to other plants without any TAW. Plant size, measured by total employment, went from 60 to 65 workers for plants without TAW. For plants with at least one agency worker, the number of employees went from 139 to 219. The difference of employment between plants with and without TAW, before and after the reform, is 74 employees.

[TABLE 1 HERE]

Most of these figures hold if we measure size in terms of log output or log value added; likewise, all these differences are statistically significant. With any of these measures, plants using TAW are larger than plants without TAW in the pre-reform period, and the difference in size increases during the post-reform period

Motivated by the idea that inventories could be used to cope with volatility (Christiano, 1988), we also look at the value of the inventories over the total value of sales. We observe that plants with TAW on average have larger inventories than firms without TAW. This difference is 1.8 percentage points during the pre-reform period, although only statistically significant at 7%. This difference increases to 2.7 percentage points in the post-reform period, an increase that is significant at 1% risk level. We think that this aggregate pattern is consistent with the idea that, in order to deal with volatility, some businesses substituted TAW with inventories during the post-reform period (although the pre-post-difference is not significant at standard levels).

Finally, the data also exhibits large heterogeneity with respect to the number of plants and agency worker shares in each sector. The largest sector in terms of number of plants and output is the *Manufacture of food products and beverages* (ISIC 15). Regarding the share of TAW, the subsector *Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials* (ISIC 20) has the largest number of temporary agency workers. Finally, the sector with the most changes in the share of TAW is the *Manufacture of basic metals* (ISIC 27), which rose from 7.6% in 2002 to 28.1% in 2006 and then fell to 5.6% in 2010.

4. *Main Empirical Results*

We present the empirical analysis in two parts. In the first, we analyze the determinants of the demand for TAW with a focus on plant size and volatility. In the second, we study the regulation's effects on several measures of plant performance such as employment, value added, output, and use of inventories.

4.1. Determinants of the Demand for Agency Workers

Overcoming past data limitations, this section sheds some light on the relationship between TAW and plant characteristics. Specifically, we identify volatility and size as important characteristics of plants that use TAWs. Figure 3 presents the relationship between the share of agency workers and both size and volatility. We compute plant size as total employment and volatility as the 5-year standard deviation of log change in value added.[10] We divide plant-year observations into 20 quantiles by size (Panel A) and volatility (Panel B).

[FIGURE 3 HERE]

Panel A presents the relationship between the share of temporary workers and plant size. The smallest 5% of plants use on average only 1% of temporary agency workers, while the largest 5% use more than 11% of TAW. There is also a steep monotonic relationship between plant size and the use of at least one TAW. In the lowest quintile, only 2.6% of plants use TAW, whereas in the largest quintile more than 45% of plants use TAW. However, when focusing on the share of TAW conditional on having agency employees, we observe a U shape, without substantial differences across quintiles. As mentioned previously, we interpret these patterns as suggestive evidence of fixed costs for hiring agency workers. Plant size is correlated with TAW use but not with its intensity (share of TAW). Indeed, we think it is reasonable to assume economies of scale in both i) the management of contracts between the user firm and the agency that provides agency workers and ii) the supervision of the agency/agencies by the user firm.

The Chilean manufacturing data also shows a strong monotonic and positive relationship between volatility and the share of TAW. For plants in the lowest quantile of volatility, the share of agency workers is the smallest (2.2%), while for plants in the 20th quantile, the average share of TAW is the largest (7%). If we use a weighted average (by employment) in each quantile, the percentage of TAW in the first quantile of volatility is only 1%; for plants in the top quantile, the figure is 16%. Moreover, plants that face higher volatility have a higher probability of hiring at least one TAW, relative to plants that faced lower volatility. This

[10] Specifically, we compute: $SD(dvla) = \left(\sum_{h=1}^{5}\left(dlva_{t-h} - \overline{dlva}_{t-5,t-1}\right)^2/5\right)^{1/2}$

difference goes from 11% in the first quantile to 22% in the last quantile. Finally, conditional on hiring at least one agency worker, the simple average of the TAW share is also lower in the first quantile (around 20%) than in the 20^{th} quintile (31%). All of these results are in line with the idea that plants use TAW to cope with volatility, as has been suggested by previous research (e.g. Jahn and Bentzen, 2010; Hirsch and Mueller, 2012). Figure 4 summarizes these findings in a contour diagram where the x-axis represents plant volatility and the y-axis plant size.

[FIGURE 4 HERE]

As expected, smaller plants that face low volatility do not use temporary agency workers, while the share of TAW is higher in large firms that face a significant level of volatility.[11] Based on these findings, we build our empirical analysis on two ideas. First, plants keep a share of TAW to cope with volatility. Second, the hiring cost of TAW has both variable and fixed components: the former mainly related with the payroll and the latter associated with economies of scale in both the management of contracts between the user firm and the agency that provides TAWs and the supervision of the agency by the user firm.[12]

To formally study the relationship between plant characteristics and the share of TAW, we use a Tobit model. We start by assuming that the observed TAW share is equal to a latent variable whenever the latent variable is above 0 and below 1, as follows:

$$Sh\widetilde{TAW}_{i,j,t} = \alpha_j + \alpha_t + \alpha_2\sigma_{i,t} + \alpha_3 Size_{i,t} + \beta'\boldsymbol{X}_{i,j,t} + v_{it}$$

$$ShTAW_{i,j,t} = \begin{cases} 0 \; if \; Sh\widetilde{TAW}_{i,j,t} < 0 \\ 1 \; if \; Sh\widetilde{TAW}_{i,j,t} > 0 \\ Sh\widetilde{TAW}_{i,j,t} \quad otherwise \end{cases}$$

[11] This result holds independently of how we proxy volatility (log change of VA, output, or employment) and size (total employment, output, or value added).

[12] From the literature, we know there are other reasons to hire TAW, for example, to improve the labor matching process or to reduce labor costs bypassing some employment protection laws. We think, however, that these factors are related to the plant's volatility: the matching process is more important in a firm that must be hiring workers continuously, and one of the protection laws that companies try to bypass is associated with the cost of hiring/firing workers.

Eq. [2]

where $Sh\widetilde{TAW}_{i,j,t}$ and $ShTAW_{i,j,t}$ are the latent variable and the observed share of TAW in plant i of sector j (3 digit ISIC code rev.3) in year t. For simplicity, we assume that the latent variable is a linear function of plant volatility $\sigma_{i,t}$, plant size $Size_{i,t}$, a set of control variables $\boldsymbol{X}_{i,j,t}$, and fixed effects at time and sector levels.

We worked to construct an instrument for plant-level volatility that gets rid of bi-directional causality, which can occur because on one hand, firms use TAW to cope with volatility, but on the other, the use of TAW might affect how value added reacts to shocks because TAW provides flexibility. To deal with this problem, we predict the log change of value-added by using input shares at the plant level multiplied by the log change in the price of inputs, and by using the exports share and the imported inputs share multiplied by the log change in the real exchange rate.[13] Under the assumption that firms are price takers, we compute the five years' standard deviation of the predicted log change in value added $\widetilde{dlva_{\imath\jmath t}}$ to use as our proxy for volatility.[14]

As long as plants are price takers, the proxy for volatility that we obtain is exogenous to the firm, and therefore we do not have reverse causality; but we still have to control for the effect of a shock on the decision of using additional agency workers in the short run. For example, if a firm receives a large exogenous transitory positive shock, both the demand for TAW and our measure of external volatility might increase in the short run. To avoid having the volatility coefficient capture this effect, we include the current log change and two lags of the predicted log change of value added in our Tobit model.

We believe the size coefficient in equation [2] captures the economies of scale in the hiring process of TAW. For estimation, we use the fourth lag of the log total employment as proxy for plant size ($Size_{i,j,t} = lemp_{i,j,t-4}$) instead of the current level to avoid the reverse causality

[13] In particular, we estimate Equation [C1] presented in Appendix C. Appendix C describes our approach in more detail and it also provides evidence of the reverse causality issue (plants using TAW react more to external shocks).

between short-term demand changes and the share of TAW around its average/expected level.[15] Finally, to avoid any remaining omitted variable bias when estimating in equation [2], we include time and sector dummies, the manufacturing wage index, the energy prices price index, and the real exchange rate index. We interact all of these indexes with the plant's labor share, energy shares, export shares, and input imported shares, respectively.

Table 2 presents our estimates of equation [2] using the proxies for volatility and plant size. For completeness, we also include the results from a Probit model that uses an indicator variable equal to one if the plant hires at least one TAW $(TAW_{ijt} > 0)$. Standard errors are clustered at the time-sector level because the proxy for volatility uses the same log change of input prices and real exchange rate for all firms in each year. In addition, it uses the same log change of sector price each year in each sector. Therefore, error terms could be correlated at the year-sector level.[16]

[TABLE 2 HERE]

We have 27,097 plant-year observations for the period 2001-2011. Column (1) shows results from the Tobit model. The coefficient for volatility is 0.72 and is significant at 1%. Plants with higher volatility use more TAW. A one standard deviation increase in volatility (0.026) implies a 0.019 increase in the share of TAW, an economically significant impact if we consider that the average share of TAW in the sample is 0.042, and the average share of TAW conditional to have at least one TAW is 0.237. Focusing on the economies of scale, the coefficient for the size variable is 0.10 and is significant at 1%. A one standard deviation increase in a plant's size (1.18) implies a 0.118 increase in the share of TAW.

Column (3) shows the estimates of the Probit model. Volatility and size increase the probability of hiring at least one TAW. At the mean values, a one standard deviation increase in volatility implies a 0.7 percent increase in the probability of having at least one TAW, a modest economic

[15] Firms may hire additional TAWs to deal with the immediate effects of a transitory positive shock. In that case, we would find a correlation between having TAW and the plant´s size that is not related with the economies of scale in hiring agency workers, but with the economic cycle.

[16] Results remain statistically significant at standard levels when we cluster standard errors at the plant level.

effect since the simple average in the sample is 18 percent. Also, clustering at the plant level (non-reported results), this result is significant only at 19%. For size, the coefficient is 0.31 and is significant at 1%, either clustering at the sector-year level or at the plant level. This result implies that a one standard deviation increase in size implies an 8 percent increase in the probability of using TAW.

Column (2) and (4) study if there is a change in the use of TAW before and after the 2007 regulation. We find that after the reform, plant size became more important to explain both the share of TAW and the probability of having at least one TAW. Focusing on volatility, from the Tobit and Probit models we obtain positive estimates for volatility and the interaction between volatility and the post-reform dummy. Results are statistically significant at standard levels only for the share of TAW, although in both models, the joint test for volatility and volatility interacted with the post-reform dummy rejects the null hypotheses that both coefficients are equal to zero.

If previous results on size are due to an increase in fixed cost, we should expect that plants closer to the threshold that triggers the use of TAW are the most affected by the reform. Figure 5 presents the evolution of the percentage of plants with at least one agency worker for four groups of plants with different sizes. We divided all plant-year observations in four groups by size (4th lag of total employment). The share of plants with TAW falls in all groups after the reform. For the first group, which includes the smallest plants, the fraction of plants with at least one TAW falls from 0.084 before the reform (2004-2006) to 0.054 after the reform (2007-2009), a 36% reduction. For the second group, this fall is 26%, and for the third, it is 22%. For the fourth group, which includes the largest firms, the percentage of TAW-user plants falls only 5%.

[FIGURE 5 HERE]

In sum, we find strong evidence that firms use TAW to cope with volatility. Plants subject to higher degrees of exogenous volatility tend to hire more agency workers. Second, we find suggestive evidence that there are fixed costs to hiring agency workers. The share of plants using TAW increases with different measures of plant size, and size becomes more important as a determinant of TAW use after a labor reform that increased the cost of using this type of employment.

4.2. Effects of the TAW regulation on Plant Performance.

Next, we study the effects of the regulation at the plant level. We compare plants that used TAW before the reform *vis-à-vis* plants that did not use agency workers. We also distinguish effects by the intensity of TAW use (i.e. share of TAW) and show the robustness of our results. We begin with the following model:

$$\log Y_{it} = \alpha_i + \nu_t + \beta_1 (DTAW_{i\ PreRef} \cdot t) + \beta_2 (DTAW_{i_{PreRef}} \cdot DRef) + \rho' \boldsymbol{X}_{it} + \epsilon_{it}$$

Eq. [3]

Where $\log Y_{it}$ represents the logarithm of the outcome variable in plant i at time t, $DRef$ is a post-reform dummy, and $DTAW_{i_{PreRef}}$ is a binary variable equal to 1 if the plant used TAW before the reform in 2006. We account by selection on time invariant characteristics by including plant fixed effects α_i, and we also allow TAW-user plants to have a specific time trend ($DTAW_{PreRef} * t$). Moreover, we include year fixed effects to account for the economic cycle and a set of additional variables $\boldsymbol{X}_{ijt}$ that control for changes in the real exchange rate and input prices.

While the previous model distinguishes between TAW user and non-user plants, it does not control by the intensity of use of agency workers. To account for this source of variation, we also estimate the following specification à la Card and Krueger (1994):

$$\log Y_{it} = \alpha_i + \nu_t + \beta_1 (\%TAW_{i\ PreRef} \cdot t) + \beta_2 (\%TAW_{i_{PreRef}} \cdot DRef) + \rho' \boldsymbol{X}_{it} + \epsilon_{it}$$

Eq. [4]

where $\%TAW_{i\ PreRef}$ stands for the share of TAW in plant i before the reform in 2006. Variation in this variable accounts for differences between user and non-user firms while simultaneously accounting for differences within the set of TAW users before the reform. Indeed, as we show below, the value of $\%TAW_{i\ PreRef}$ is a strong predictor of the actual proportional adjustment before-after the regulation.

In both specifications, the coefficient of interest is β_2. Table 3 presents the estimates of this coefficient from several specifications. This table is organized into six result modules, one for each outcome variable. Within each module (I to VI), we report the $\widehat{\beta_2}$ obtained when estimating equations [3] and [4] using different sets of controls (from a baseline that only includes controls and year fixed effects to the most complete specification with controls, year fixed effects, a TAW-user-specific trend, and plant fixed effects).

[TABLE 3 HERE]

Across all specifications, module I shows a positive and significant effect on the share of regular workers (non-agency employment), which gives us reason to be confident about using the TAW reform as a source of variation for identification. According to our preferred specification (3), which controls for unobserved time invariant plant characteristics and TAW-user-specific time trends, we estimate that TAW-user plants experienced an increase of 10.4 percentage points (on a base of 80%) in the share of non-agency workers. Moreover, among TAW-user plants, total employment decreased by 6.8% (relative to non-TAW user plants) after the reform (see module II), a significant decrease considering that their number of non-agency workers increased by 9% on average, as shown by module III.

All these effects on employment go in the same direction and are also statistically significant when we estimate Eq. [4]. From our most complete specification, we conclude that, for plants using agency workers before the regulation, one standard deviation in the share of TAW not only increased the share of non-agency workers by 13% and the number of non-agency workers by 20%, but also decreased total employment by 9% during the post-reform period.

Table 3 also shows a negative effect of this reform on output (module IV), which decreased by 5.7% in TAW-user plants, and an increase in the inventories share of 1.7 percentage points on a base of 22%. However, these $\widehat{\beta_2}$ coefficients for inventories are noisier (see module VI). Finally, although we estimate a negative effect on value added using the base specification (1.), the coefficient is positive and non-statistically significant when we include a TAW-specific trend and plant fixed effects. Thus, as follows from module V of Table 3, this latter result is non-robust.

Overall, these results suggest that the TAW reform triggered a substitution effect towards the relatively less expensive type of workers. This effect is shown by the increase in the share of non-agency workers during the post-reform period. However, and despite the substitution of workers, plants using TAW before the reform saw a decrease in their total employment and output relative to non-TAW user plants. We also find some modest evidence of an effect on inventories, which could act as another substitution channel as long as agency workers were actually used to deal with volatility. However, we do not find evidence of any effect on value added.

The previous set of results exploits variation that arose from the 2007 regulation and its interaction with the use –and intensity of use- of agency workers. However, the use of agency employment is a choice made by each plant, which might raise concerns of selection bias. In what follows, we discuss the extent to which the estimated effects could be confounded by pre-determined differences between TAW-user and TAW-nonuser plants, and in section 5, we try to address any remaining concerns by performing different robustness checks.

We explore the extent to which the previous results could be confounded by selection of plants into using (or not using) agency workers. To do so, we estimate the following event-study type of model:

$$\log Y_{it} = \alpha_i + \nu_t + \sum_{s=2002}^{2011} \beta_s (DTAW_{i_{PreRef}} * Year_s) + \rho' \boldsymbol{X}_{it} + \epsilon_{it}$$

Eq. [5]

where the $\widehat{\beta_s}$ coefficients capture the year-by-year difference in the outcome variable between TAW-users and nonusers after accounting for plant and year fixed effects as well as price controls. This approach allows us to check and discuss the identification assumptions behind our main results. For instance, if we observed that plants using TAW before the reform were also decreasing total employment (relative to nonusers of TAW), then we should be worried that the negative effect on total employment for TAW-user plants simply reflects differences in pre-trends between these two groups of plants (instead of the effect of the reform). Figure 6 plots the point estimates and 95% confidence intervals for these β_s coefficients.

[FIGURE 6 HERE]

We observe that during the pre-reform period, total employment and output were growing in TAW-user plants. After the reform, however, these trends broke. This pattern, which looks like a reflection of the classical Ashenfelter's dip, suggests that the coefficients on the $DTAW_{i_{PreRef}} \cdot DRef$ term might be downward biased, underestimating the effects for total employment and output. That would be the case if some plant level -time variant- unobservable is positively correlated with both the use of agency workers and total employment. In that case, a first order approximation for the counterfactual evolution of total employment and output in these plants would indicate that, in absence of the reform, these plants should have kept experiencing growth. A similar analysis can be done for the share of non-agency workers for which the effect might also be a downward bias. This line of thought would also suggest that our previous results are a conservative approximation of the effects of the TAW regulation on total employment, output, and the share of agency workers, an issue that we address from different perspectives in the next section. Regarding other variables, we feel confident that -under the standard difference in difference pre-trends assumption- the estimated effects on log value added, the log of non-agency employment, and the share of inventories are unbiased.

5. Robustness Analysis.

In this section we perform several robustness checks using different estimation approaches. We first estimate exposure effects in subsection 5.1. To do so, we classify TAW-user plants into two groups according with their pre-reform share of agency workers. Then, we separately estimate differences of those groups with respect to non-TAW user plants and compare differences exclusively among TAW-user plants. In section 5.2, we estimate a model in first differences to include lagged dependent variables and plant fixed effects in an attempt to control for pre-trends, as suggested in Angrist and Pischke (2009). We complement this exercise by estimating a model that accounts for both time variant and time invariant unobservables at the plant level. Finally, in section 5.3, we implement a control function approach that accounts for unobservable plant characteristics that are associated with the decision to use agency workers; and we also complement this approach with a two-stage least squares strategy.

5.1. Exposure effects: Reform and intensiveness of TAW use.

In this subsection, we decompose the $DTAW_{PreRef} = 1$ classification into two complementary groups. We create the dummy $DTAW_{PreRef}^{Low\%}$, which equals one for plants that used TAW before the reform and had a share of TAW below the median in 2006 (zero otherwise), and we also create the dummy $DTAW_{PreRef}^{High\%}$, which equals one for plants that used TAW before the reform and had an average share of TAW above the median in 2006 (zero otherwise). We embedded these variables in the main model (Eq [3]) as follows:

$$\begin{aligned}\log Y_{it} = \alpha_i + \nu_t + \beta_1 \left(DTAW_{i\,PreRef}^{High\,\%} * t\right) \\ + \beta_2 \left(DTAW_{i\,PreRef}^{Low\%} * t\right) + \beta_3 \left(DTAW_{i\,PreRef}^{High\,\%} * D_{t>200}\ \right) \\ + \beta_4 \left(DTAW_{i\,PreRef}^{Low\,\%} * D_{t>2006}\right) + \rho' \boldsymbol{X}_{it} + \epsilon_{it}\end{aligned}$$

Eq. [6]

where the coefficients on $DTAW_{PreRef}^{Low\%} * D_{t>2006}$ and $DTAW_{PreRef}^{High\%} * D_{t>200}$ capture the differential effect of the reform for plants with a High and a Low share of TAW, with respect to the baseline of not using TAW ($DTAW_{PreRef} = 0$).[17] This specification is helpful in two ways. First, it allows us to study the effects of the reform among groups exposed to different intensities of treatment, and second, it allows us to confirm that the identification of our main results actually come from the reform on agency workers. In other words, if previous estimates are really driven by the regulation on TAW, then we should expect stronger effects on plants that were using a larger share of TAW before the reform.

Table 4 below presents the results obtained after estimating Equation [6] in two samples: a sample with all plants and a sample that only considers plants that were using TAW in 2006.

[TABLE 4 HERE]

From the comparison between columns (1) and (2), it follows that the effect of the reform on employment is larger for plants that were more exposed to the TAW regulation (those with a larger TAW share). Reassuringly, column (3) confirms that—despite the small number of observations in each group and the *de facto* double number of controls *vis-à-vis* the regression with all plants—[18]those differences are also statistically significant among TAW-user plants for total employment, for non-agency employment, and for the share of non-agency employment. However, the same pattern is not followed by the output variable, which decreased by a similar amount in high intensity and low intensity TAW users (relative to non-users). Consistently, the coefficient for the differential effect among TAW-user plants on output is indistinguishable from zero. Regarding the effect on the share of inventories over output, we observe that the effect is actually stronger for plants with a more intensive use of TAW, but it is not a statistically significant difference from zero at the standard levels. Finally, these results also confirm the zero effect of the reform on value added.

5.2. Lagged Dependent Variable and Plant' Specific Trend.

[17] Although this framework is easily extensible to more quantiles, we split the sample of $DTAW_{PreRef} = 1$ just in two groups (above and below the median) to maximize power, given the reduced number of observations within $DTAW_{PreRef} = 1$ (approximately 1000 plants in each group, as of 2006).

[18] Restricting the sample exclusively to plants that are TAW-user (pre-reform) is equivalent to including controls interacted with a pre-reform TAW-user plant dummy in the full sample.

In this section, we estimate two alternative models. First, to account for pre-trends we include the lag of the dependent variable as a control, as follows:

$$\log Y_{it} = \alpha_i + \nu_t + \theta Y_{it-1} + \beta_1 \left(DTAW_{i\ PreRef} \cdot t\right) + \beta_2 \left(DTAW_{i_{PreRef}} \cdot DRef\right) + \rho' \boldsymbol{X}_{it} + \epsilon_{it}$$

where Y_{it-1} represents the first lag of the outcome variable. To estimate this model, we take first differences and instrument ΔY_{it-} with ΔY_{it-h} for $h > 1$ because ΔY_{it-1} is mechanically correlated with $\Delta\epsilon_{it}$. Thus, we end-up estimating the following specification:

$$\Delta \log Y_{it} = \nu_t + \theta \Delta Y_{it-1} + \beta_1 \left(DTAW_{i\ PreRef}\right) + \beta_2 \left(DTAW_{i\ PreRef} \Delta DRef\right) + \rho' \Delta \boldsymbol{X}_{it} + \Delta\epsilon_{it}$$

Eq. [7]

where, following the literature, we instrument ΔY_{it-1} with ΔY_{it-2}. Moreover, we also estimate a model that allows the effect of unobservables on plant performance to change over time (i.e. plant-specific time trend), as follows:

$$\log Y_{it} = \alpha_i + \nu_t + \mu_i \cdot t + \beta \left(DTAW_{i_{PreRef}} \cdot DRef\right) + \rho' \boldsymbol{X}_{it} + \epsilon_{it}$$

where α_i controls for time invariant plant characteristics and $\mu_i \cdot t$ controls by time variant plant characteristics. In practice, we take the first difference and estimate the following difference model with plant fixed effects:

$$\Delta \log Y_{it} = \nu_t + \mu_i + \beta \left(DTAW_{i_{PreRef}} \cdot \Delta DRef\right) + \rho' \Delta \boldsymbol{X}_{it} + \epsilon_{it}$$

Eq. [8]

As mentioned by Gorodnichenko and Sabrianova (2007), applying fixed effects to a differenced equation not only tends to magnify standard errors due to a smaller sample size, but also reduces residual variation in the regressors, thereby increasing the variation of the error term, which might create attenuation bias due to an increase in the noise-to-signal ratio. Table 5 below presents our estimates from both models:

[TABLE 5 HERE]

Again, the sign and magnitude of the estimated effect of the reform on employment is fairly robust to both of these alternative models. Regarding the effect of the reform on output, it is still negative for the model with lag dependent variable, but weaker (-3% with a t-stat of 1.8) and non-statistically different from zero for the model described by Equation [8], a fact that might arise from attenuation bias. Although we find a positive sign for inventories, as in previous exercises, these estimates cannot reject a zero effect of the reform on this variable. Again, we do not find any significant effect for value added.

5.3. Accounting for Selection: A Control Function Approach

In this section, we explicitly account for the selection of TAW users. We do so by implementing a semi-parametric approach and a standard two-stage least squares estimation. The goal is to obtain consistent estimates for the effects of the reform after controlling by unobservable characteristics that influence a plant's decisions about using TAW. To begin, we model the decision of using TAW pre-reform as follows:

$$DT\widetilde{AW_i^*}_{2006} = \psi(\boldsymbol{Z_i}) + \epsilon_i$$

$$DTAW_{i_{2006}} = \begin{cases} 1 & if\ -\psi(\boldsymbol{Z_i}) < \epsilon_i \\ 0 & if\ -\psi(\boldsymbol{Z_i}) \geq \epsilon_i \end{cases}$$

where the observed choice $DTAW_{i_{2006}}$ depends on a latent variable $DT\widetilde{AW_i^*}_{2006}$ describing the benefits of using TAW. As in the previous sections, we define $DTAW_{i_{2006}} = 1$ if a plant uses TAW in 2006 (right before the reform) and zero otherwise. As discussed earlier, this definition could induce bias in our estimates, especially if the use of TAW is prone to mean reversion. To address this concern, we need a variable vector $\boldsymbol{Z_i}$ shifting the decision of using TAW in 2006. As $\boldsymbol{Z_i}$, we use a set of controls that include price variables $\boldsymbol{X_{it}}$ and an indicator for whether a plant used TAW in 2002 ($DTAW_{i_{2002}}$). Finally, we assume that the term ϵ_i, which represents plant-level heterogeneity, is drawn from a normal distribution (i.e. $\epsilon_i | Z_i \sim N(\mu, \sigma)$).

In this setting, identification will be achieved under the assumption that $\epsilon_{i2002} \perp \epsilon_{i2006}$. In other words, we need to assume that $DTAW_{i_{2002}}$ works as a good instrument for $DTAW_{i_{2006}}$, which should be true if the effect of transitory shocks on the use of agency workers dissipates "soon enough". The semi-parametric model that we just described allows us to recover the $E[\epsilon_i|\boldsymbol{Z_i}, DTAW_i]$ from a Probit specification for $DTAW_{i_{2006}}$, which then we can use as a control in our main specification, as follows:

$$\log Y_{it} = \alpha_i + \nu_t + \beta_1(DTAW_{2006} \cdot t) + \beta_2(DTAW_{2006} \cdot DRef) + \rho'\boldsymbol{X}_{it} \\ + \gamma_1(\lambda^{TAW}(\boldsymbol{Z_i}) \cdot t) + \gamma_2(\lambda^{TAW}(\boldsymbol{Z_i}) \cdot DRef) + \epsilon_{it}$$

Eq. [9]

where $\lambda^{TAW}(Z_i)$ is the generalized residual from the Probit model for $DTAW_{2006}$ (i.e. the Mills ratio) interacted with the post-reform dummy. If well-specified, this control-function approach should remove the part of the variation in $DTAW_{2006}$ that is correlated with the error term ϵ_{it}, guaranteeing that the OLS projection of the outcome on $DTAW_{2006}$ is consistent.[19] Estimates from this approach are shown in Table 6. For comparison, we also include 2SLS estimates of β_2 using $DTAW_{2002} \cdot DRef$ and $DTAW_{2002} \cdot t$ as instrument for $DTAW_{2006} \cdot DRef$ and for $DTAW_{2006} \cdot t$.

[TABLE 6 HERE]

In this case, we observe that the sign and magnitude of the estimated coefficients for total employment and output resembles the effects of the regulation shown by Table 3. We think that this should dissipate concerns about mean reversion bias for those variables. Following this approach, we estimate that post-reform TAW-user plants experienced an increase of 6 percentage points in their share of non-agency workers, a 9% decrease in total employment, and a 14% decrease in the value of output. Puzzlingly, the effect of the reform on non-TAW employment decreased from 10% to 2% and became statistically insignificant. Once again, the effects on value added and inventories are not statistically different from zero. Finally, we find

[19] It is worth noting that identification in this context also requires assuming linear dependence of mean potential outcomes on the unobservables that influence the choice.

it remarkable that - in line with Kline and Walters (2017) - the estimates obtained using 2SLS and control function are very similar to each other.

In sections 4 and 5, we have shown that plants using TAW experienced a decrease in total employment after the reform. Across different specifications, we estimate a negative effect ranging from -9% to -6%. Similarly, our results suggest that the regulation had a negative effect on plant output, with estimates within the range of -14% to -3%.[20] On top of this scale effect, we observe a labor substitution response, with an estimated increase of the share of non-agency workers within a range of 6% to 10%. The results also suggest that this increase did not come exclusively from a decrease in the use of TAW, but it might reflect an increase in the use of non-agency workers, which was larger in more exposed plants. Finally, we find only scarce evidence of plants substituting agency workers with inventories in order to deal with volatility, and there is no evidence of any effect on value added.

6. Conclusion

During the past decades, countries have witnessed rapid growth in the number of people engaged in alternative work arrangements. Here, we have studied one of the most prominent non-standard work arrangements: temporary agency work, also known as temporary help jobs. The nature of this type of employment is controversial. On one hand, some argue that temporary agency jobs allow firms to cope with volatility while helping workers to get experience and reach more stable employment. On the other hand, others claim that temporary agency employment is a trap, a strategy used by employers to circumvent labor regulations protecting workers´ rights. Reflecting on public concerns and responding to the rising importance of new forms of labor, countries have enacted new regulations that aim to balance flexibility and security in the labor market.

In this paper we have studied plant characteristics that might explain the demand for TAW and the effects of a regulation on TAW that took place in Chile during the 2000s. Our findings

[20] We interpret the fact that we could not reject a zero effect when accounting for time variant and time invariant unobservables as an attenuation bias problem.

regarding plant characteristics can be summarized as follows. First, establishments that face a volatile environment demand more TAW. Moreover, the predictive power of volatility increases after the regulation on TAW is in place, suggesting that during the pre-reform period, plants were using agency workers for reasons other than to cope with uncertainty (i.e. regulatory arbitrage or screening). Second, we find that plant size is an important explanatory variable for the share of TAW, a result that we interpret as evidence of economies of scale. In fact, the increase in costs prompted by the TAW regulation strengthened the relationship between TAW use and plant size. Regarding the effects of the TAW regulation on plant economic performance, we find evidence of both scale and substitution effects. TAW-user plants experienced an increase in their share of non-TAW employment during the post-reform period as well as a decrease in total employment and output relative to non-TAW user plants. However, we do not find evidence of any effect on value added, and we only have suggestive evidence that plants increase inventories as substitute of TAW to hedge against volatility.

Finally, it is worth highlighting that although we estimate a negative effect on total employment for TAW-user plants, our study is silent about the effects of this regulation on total welfare. Unfortunately, the available data does not allow us to address the effects that this reform had on workers; however, this is an economically important and policy-relevant question that we hope to address in future work.

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The Impact of Extended Employment Protection Laws on the Demand for Temporary Agency Workers

APPENDIX

Appendix A: Alternative decomposition of the TAW share

$$Share\ of\ TAW = \underbrace{\overline{ShTAW}_U}_{Intensive\ Margin} \times \underbrace{ShN_U \times \frac{\bar{l}_U}{\bar{l}_M}}_{Extensive\ Margin} \times \left(1 + \underbrace{\frac{1}{N_U}\sum_{i \in U} \frac{ShTAW_i - \overline{ShTAW}_U}{\overline{ShTAW}_U} * \frac{l_i - \bar{l}_U}{\bar{l}_U}}_{Covariance\ Term}\right)$$

Eq. [A]

Where:

$\overline{ShTAW}_U$: Simple average of TAW Share in plants with at least one TAW.

$N_U\ and\ ShN_U$: Number and Share of TAW-user plants.

$l_i\ , \bar{l}_U\ and\ \bar{l}_M$: Plant i size (total employment), the average size of TAW-user plants and the average size of all plants in manufacturing, respectively.

The covariance term accounts for the correlation between the plant share of TAW and the plant relative size among agency users. If large plants use more TAW, then this coefficient is positive; zero if there is no correlation between size and the share of TAW; and negative if small plants have a higher TAW share than larger firms.

[TABLE A1 HERE]

Appendix B: Data

This appendix provides the details of data construction. We use the Annual National Industrial Survey (ENIA) carried out by the National Institute of Statistics of Chile (INE) for the years 1995 through 2011. This survey covers the universe of Chilean manufacturing plants with 10 or more workers. The dataset also includes plants with fewer than 10 employees if these plants had 10 or more employees in previous years. A plant is not necessarily a firm, since they may have several plants; however, a significant percentage of plants in the survey are actually single-plant firms. The INE updates the survey annually by incorporating new plants that started operating during the year and excluding those plants that stopped operating for any reason, generating an unbalanced panel that follows plants over time.

For each plant, the ENIA collects data on production (value of output), value added, total employment, and wages (for regular and agency workers), exports, electricity, fossil fuel (oil and gas), direct import of inputs, and other plant characteristics. The ENIA classifies plants according to the 3-digit ISIC (Rev. 3) code and the Institute of Statistics (INE) produces 3-digit level price deflators and a manufacturing real wage index. The latter index accounts for composition effects and therefore is a best proxy for the log change of the cost of labor. For our analysis, we deflate all nominal variables by the annual average Consumer Price Index (output, value added, nominal exchange rate, etc.).

Although the INE collects quarterly data for employment, we decided to use annual data because other variables have annual frequency, and quarterly data is highly correlated within years.

The ENIA uses the following classification for labor at the plant level:

A. Employees with direct contract	B. Employees without direct contract:
A1.-Owner and managers A2.-Skilled and Unskilled Blue Collar Workers A3.-White collar workers	B1.- Skilled and unskilled Blue Collar agency workers B2.- White collar agency workers B3- Sales outsourcing

In our analysis we define “total employment” as A + B, and we define temporary agency workers as B1+B2. We do not consider sales outsourcing because we focus on temporary agency workers who are substitutes for regular workers. We also construct the following variables:

- *Plant level inventories share* as the average annual value of the plant´s stock (at the beginning of the year and at the end) over the plant´s annual output.
- *Plant level export and import shares* as the three years moving average of the ratio of nominal exports and over nominal production and direct import of inputs over nominal production, respectively.

- *Plant level input shares for labor, electricity, fuel and natural gas* as the "whole period" simple average of the expenditure in each input divided by output.

Table B1 below presents some descriptive statistics of the dataset we use.

[TABLE B1 HERE]

Appendix C: Plant's Volatility and TAW use

Equation [C] presents the model used to compute the predicted log change in value added ($\widehat{dlva}$):

$$dlva_{ijt} = \alpha_t + \alpha_j + \alpha_1 ShL_{ij} dlw_{manf,t} + \alpha_2 ShE_{ij} dlPe_{eco,t} + \alpha_3 ShO_{ij} dlPoil_{eco,t} + \alpha_4 ShExp_{ijt} dlRER_t + \alpha_4 ShImp_{ijt} dlRER_t + dlDef_{jt} + dlva_{ijt-1} + \mu_{ijt} \quad \text{Eq. [C]}$$

where $dlva_{ijt}$, Shx_{ij} and $dlPx_{j,t}$ stand respectively for the log change in value added at plant i, in sector j, at period t; the share of input $x \in$ {Labor, Electricity, Oil} in plant i of sector j (constant over time); and the log change in the price of input x (at the manufacturing level for wages and at the economy level for electricity and oil prices). $ShExp_{ijt}$ and $ShImp_{ijt}$ stand for the export and input import shares at the plant level (% of nominal output) in the last three years, and $dlRER_t$ and $dlDef_{jt}$ represent the log change in the real exchange rate (nominal exchange rate divided by local inflation) and the log change in the real price index at the three ISIC rev3 levels (from the National Institute of Statistics).

In a small open economy like Chile, plants in tradeable sectors, like manufacturing, are price takers (the average tariff in Chile is lower than 1%, and it is zero in manufacturing). Based on this, we estimate equation [C] and the predicted values for the log change of value-added at the plant level ($\widehat{dlva}$) for the period 1997-2011.[21] Following the literature, we use the second lag of the log change in value-added as instrument for the first lag in equation [C]. Table C1

[21] Although we use data since 1995, equation [C] requires us to have an instrument for the log change in value-added, so we compute equation [C] for the period 1997-2011.

below shows our results. Our composite instrument for external shock is highly significant, with an F value of 14, although it explains only 1 percent of the variance of log change of value added in our sample (R2).

[TABLE C1 HERE]

To construct our plant-level volatility instrument, we use the predicted log change in value added obtained before. For each year, we define volatility as the standard deviation of the last five lagged values of $\widehat{dlva}$ ($SD\left(\widehat{dlva}\right)$).

Table C2 explores how the presence of TAW might increase value added and output after an external shock. In column 1 we regress the log change of value added on the predicted log change value added from table C1 (our proxy for external shocks) using year and sector fixed effects. The sample period is restricted to the period for which we have data on TAW (2001-2011). Not surprising, the coefficient for our proxy for external shock is close to one (0.94)[22] with a t-statistic of 16, although the R2 is small (0.012).

In columns 2 and 3, we study the role of TAW as a shock amplifier. In column 1, the main term for our proxy for external shock is 0.81, and the interaction term of external shock and the dummy variable for the presence of TAW the previous year is positive (0.349) and statistically significant at a 1.3% level of risk. Column 3 splits plants with TAW above and below the median share of TAW. The interaction term for plants with TAW below the median has the expected positive sign (0.17), but it is not significant at standard levels. For firms with a TAW share above the median, the coefficient is larger (0.66) and significant with 99% of confidence. These results show signs of reverse causality between TAW and value added volatility (i.e. TAW-user plants react more to external shock than plants without TAW).

Finally, columns 4 and 5 show the identification power of our instrument for exogenous volatility. We perform a simple OLS estimation $SD(dlva)$ on $SD\left(\widehat{dlva}\right)$ and time and sector

[22] The coefficient is not one because we used a different sample to construct the predicted value (1997-2001).

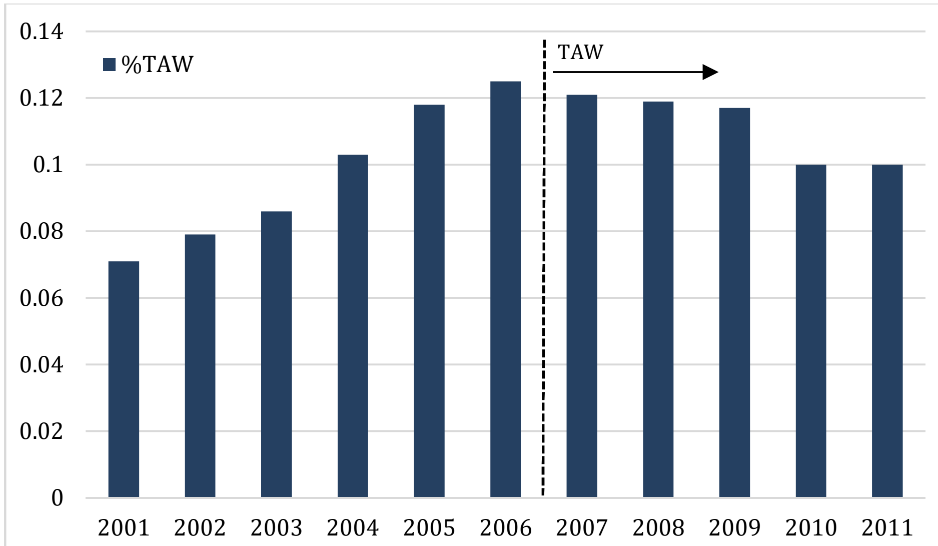
dummies. As expected, in Column 4 the coefficient for $SD\left(\widetilde{dlva_{\iota Jt}}\right)$ is positive, larger than one (1.84), and significant at 1%.[23] In Column 5, we include a dummy variable equal to one if the plants used TAW the previous year. The dummy coefficient is positive and significant at 1%, reinforcing our previous results.

[TABLE C2 HERE]

[23] Contrary to the standard deviation of the log change of value-added, the standard deviation of our external shock proxy does not include the amplification effect triggered by the employment reaction to external shocks.

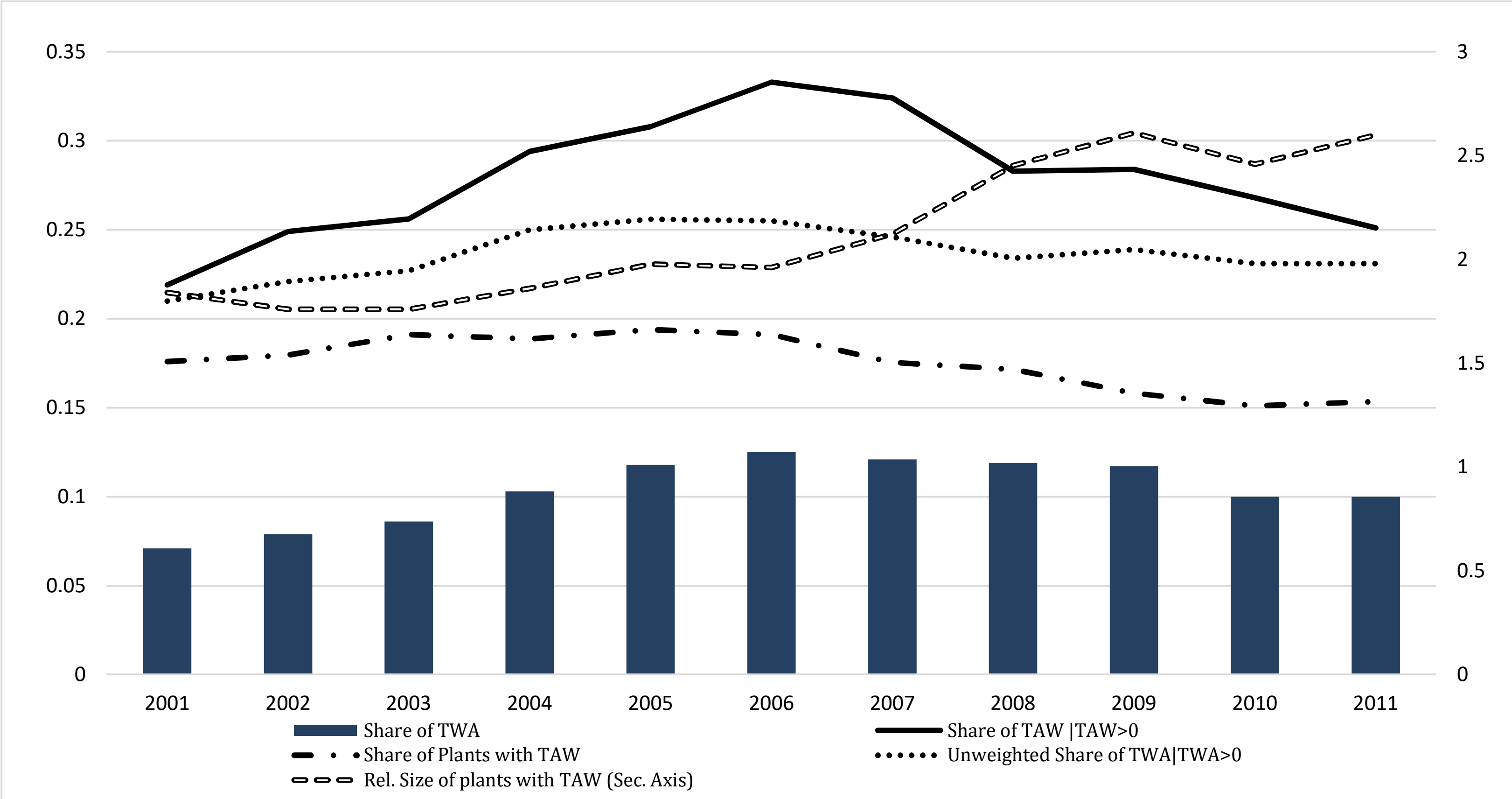
FIGURES AND TABLES

Figure 1: Share of Temporary Agency Workers in the Chilean Manufacturing Sector



Source: Authors construction using manufacturing survey.
Note: "%TAW" is a weighted average of the share of agency workers at plant level, by year. We use total employment as weight and we include all plants, with and without agency workers.

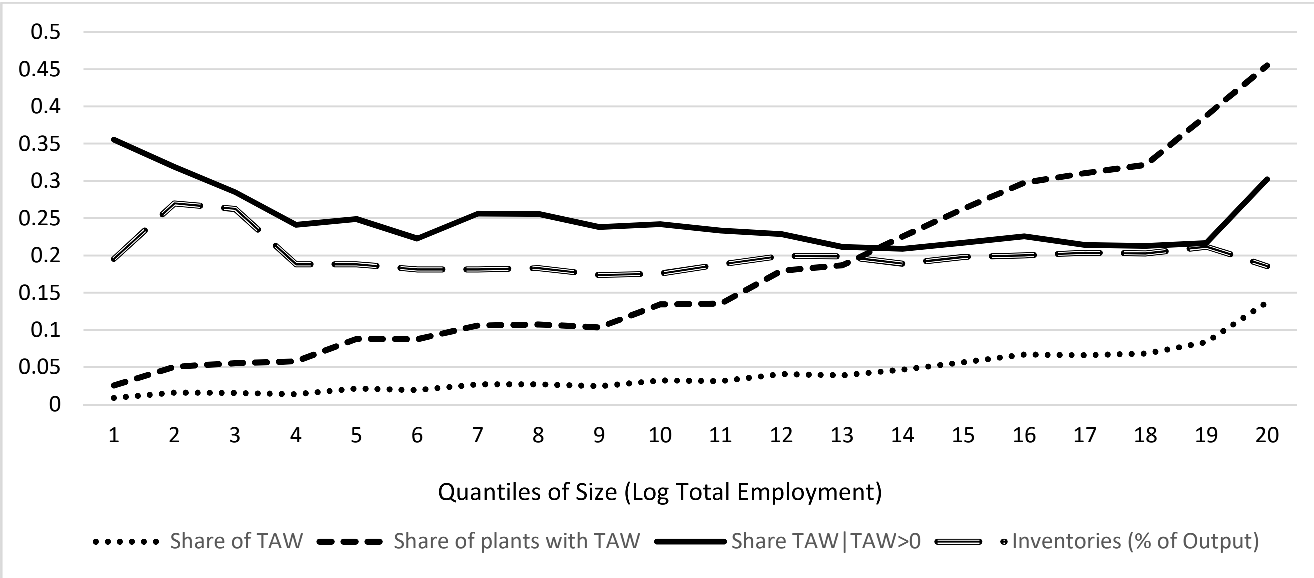
Figure 2: Share of TAW - Extensive and Intensive Margins



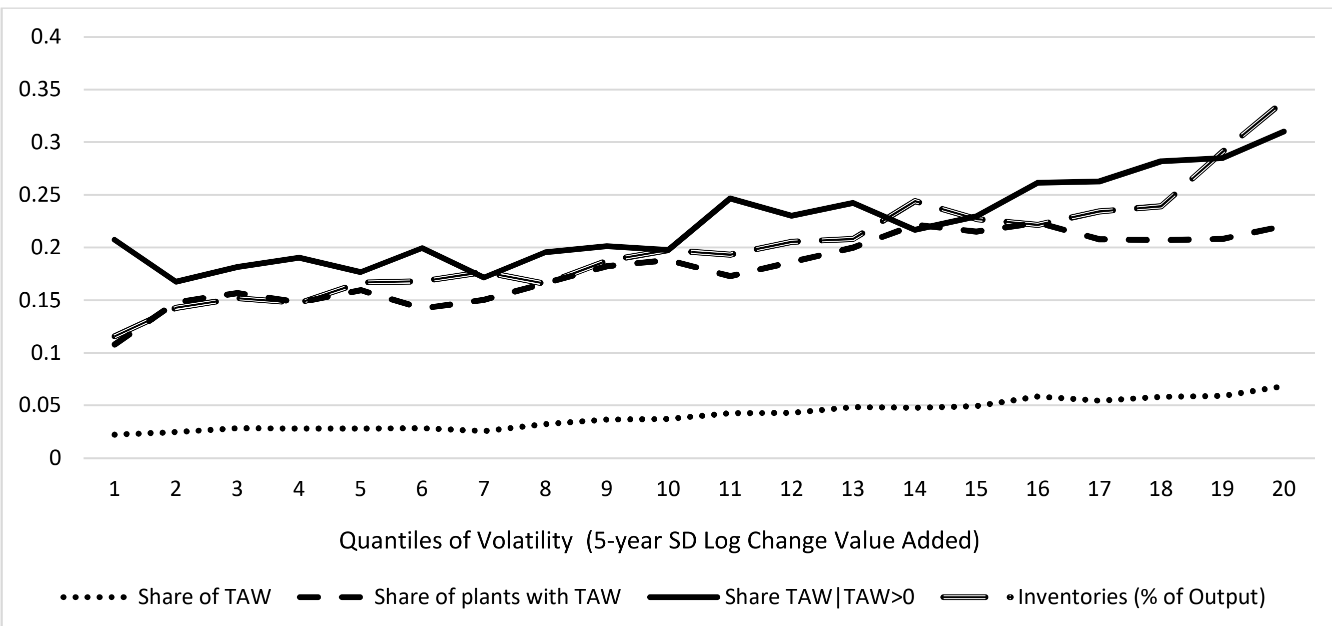
Source: Authors construction using manufacturing survey.
Note: “Share of TAW” is the average share of TAW weighted by plant´s employment. “Share of TAW | TAW>0” is the average share of TAW weighted by plant´s employment conditional on having at least one agency worker. “Unweighted share of TAW |TAW>0” is the simple average of the share of TAW conditional on having at least one agency worker. Finally, “Rel. Size of plants with TAW” is the ratio between the average size of plants with at least one agency and the average size of plants in the Chilean manufacturing sector (size measured as the total number of employees).

Figure 3: Share of TAW and Plant´s Size and Volatility

Panel A: TAW and Plant´s Size

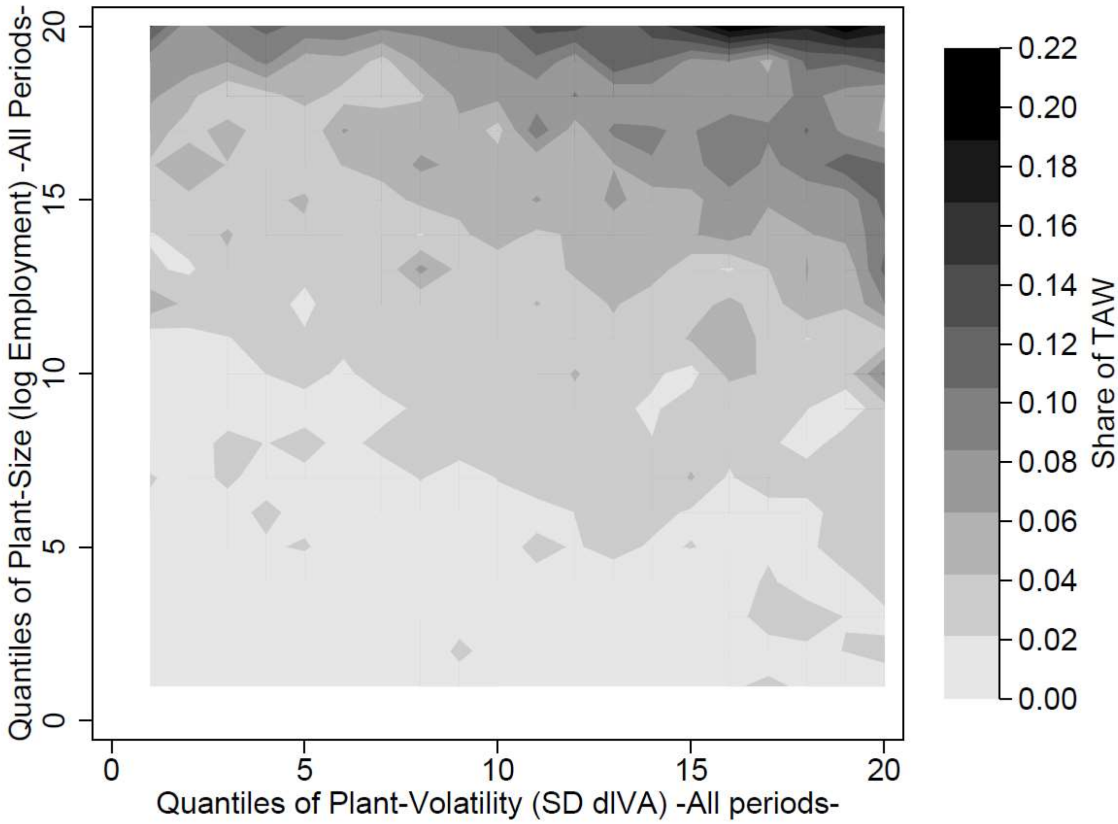


Panel B: TAW and Plant´s Volatility



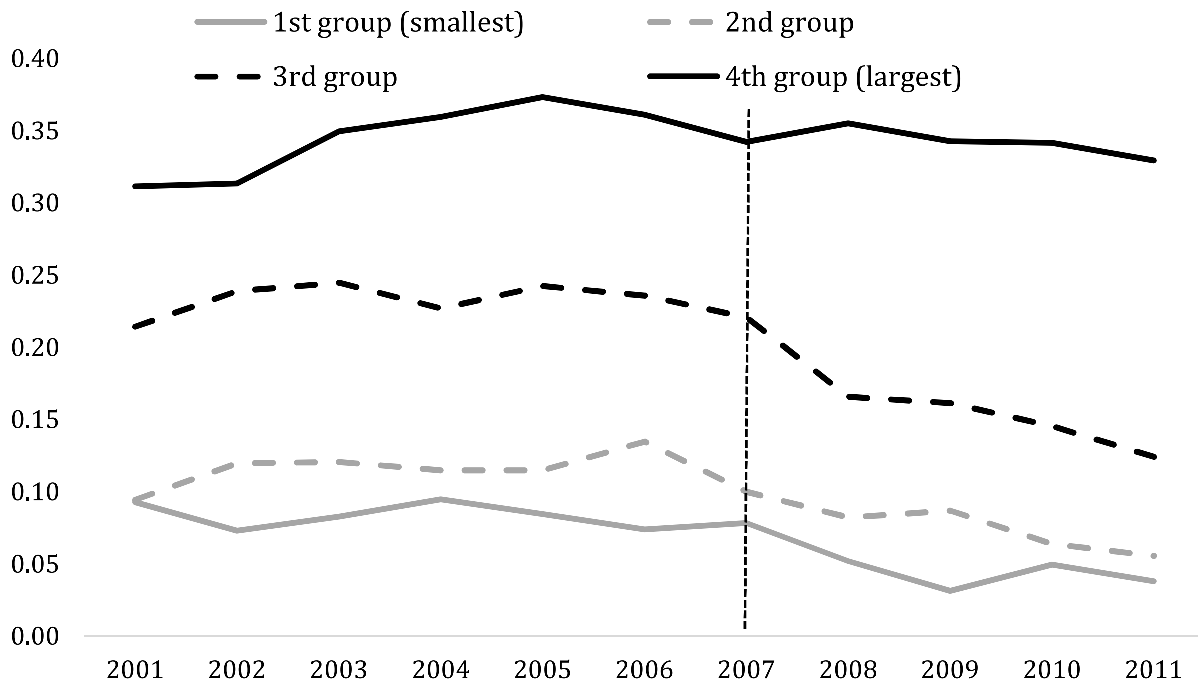
Source: Authors construction using manufacturing survey.
Note: “Share of TAW” is the simple average share of TAW in each quantile. “Share of plants with TAW” is the fraction of plants with at least one agency worker in each quantile. “Share of TAW|TAW>0” is the simple average share of TAW conditional on having at least one agency worker. Finally, “Inventories (% of Output)” is the simple average of physical inventories value as fraction of output value in each quantile.

Figure 4: Distribution of the Share of TAW by Plant´s Volatility and Size



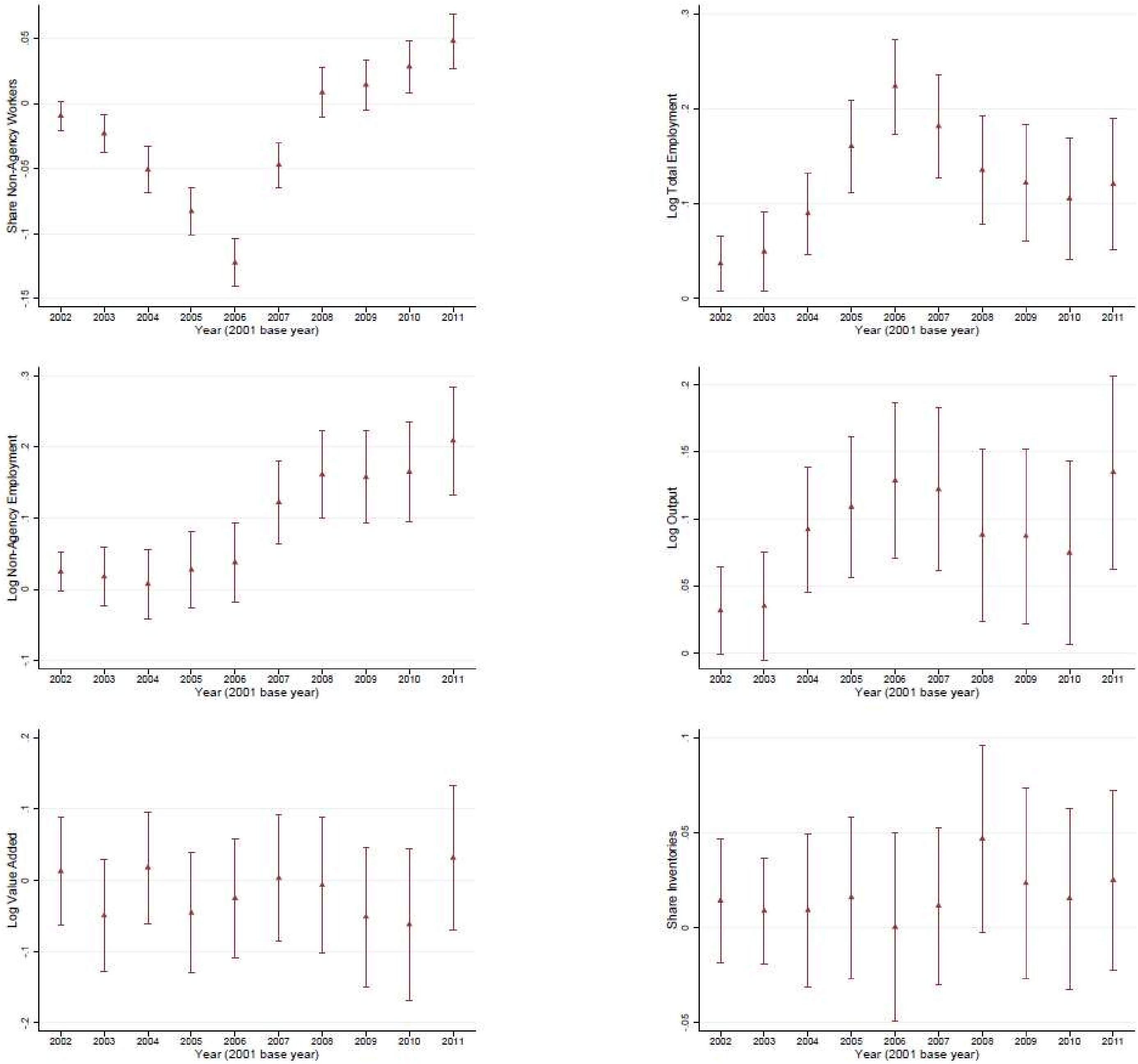
Source: Authors construction using manufacturing survey.
Note: We proxy volatility using the 5-year standard deviation of the log change of value added; for size we use the log of total employment.

Figure 5: Share of TAW within each plant size group



Source: Authors construction using manufacturing survey.
Note: We divided all plant-year observations in 4 groups by size. We defined size as the 4th lag of total employment and we compute this share on the sample that we used for the Probit estimation presented in Table 2, Column 3.

Figure 6: Event Study



Source: Authors construction using manufacturing survey.

Note: Plotted coefficients and 95% confidence intervals from specification [5] (in the manuscript). OLS estimation includes year fixed effects, firm fixed effects and a set of price controls. Robust standard errors are clustered at the plant level.

Table 1: Summary Statistics

Summary Table (Diff-in-Diff)							
Period		# Obs. {% Obs.}	Total Employment	Share TAW	Output 2006$ (Log)	Value Added 2006$ (Log)	Inv. (% Output)
Pre-Reform	With TAW=0	26075	59.656		12.881	11.771	0.203
2001-2006	Std. Dev. ()	{81%}	(0.866)		(0.011)	(0.012)	(0.004)
	With TAW>0	5992	139.444	0.237	14.047	12.905	0.221
	Std. Dev. ()	{19%}	(3.298)	(0.003)	(0.023)	(0.024)	(0.005)
Post-Reform	With TAW=0	18231	64.971		13.175	12.056	0.184
2007-2011	Std. Dev. ()	{84%}	(1.067)		(0.013)	(0.013)	(0.003)
	With TAW>0	3548	218.595	0.237	14.838	13.529	0.211
	Std. Dev. ()	{16%}	(6.578)	(0.004)	(0.032)	(0.033)	(0.007)
Difference Pre and Post-Reform							
	With TAW=0	0.02	5.315		0.294	0.285	-0.019
	Pr(|T| > |t|)		0.000		0.000	0.000	0.001
	With TAW>0	-0.02	79.151	-0.001	0.792	0.625	-0.009
	Pr(|T| > |t|)		0.000	0.034	0.000	0.000	0.360
Difference with and without TAW							
	Pre Reform	-0.63	79.788	0.237	1.166	1.134	0.018
	Pr(|T| > |t|)		0.000	0.000	0.000	0.000	0.065
	Post Reform	-0.67	153.624	0.237	1.663	1.474	0.027
	Pr(|T| > |t|)		0.000	0.000	0.000	0.000	0.010
Difference with and without TAW - Pre and Post Reform							
	Diff.	-0.05	73.836	-0.001	0.497	0.340	0.010
	Pr(|T| > |t|)		0.000	0.813	0.000	0.000	0.476

Source: Authors construction using manufacturing survey.
Note: Pr. (|T|>|t|) is the t-statistics for the mean difference.

Table 2: Demand for TAW

	Share of TAW Tobit Model		Indicator TAW>0 Probit Model	
	(1)	(2)	(3)	(4)
Volatility	0.721	0.411	1.548	1.099
	(0.231)	(0.292)	(0.618)	(0.778)
Plant Size	0.102	0.087	0.309	0.269
	(0.006)	(0.007)	(0.013)	(0.014)
Volatility x Reform		0.877		1.439
		(0.443)		(1.219)
Plant Size x Reform		0.035		0.096
		(0.009)		(0.024)
Observations	27,097	27,097	27,097	27,097
Controls	Yes	Yes	Yes	Yes
Time and Sector FE	Yes	Yes	Yes	Yes

Source: Authors construction using manufacturing survey.
Note: Estimates from Equation [2]. Robust standard errors clustered at the sector-year level in parenthesis. All specifications include year fixed effects, sector fixed effects and a set of price control variables. Volatility and Volatility x Reform are jointly significant in both models with an F-value of 7.62 in the Tobit model and an F-value of 8.57 in the Probit Model.

Table 3: Effects of the TAW Regulation

Specification	I. Change in Share Non-Agency Workers		II. Change in Log Total Employment	
	Eq.[3]	Eq.[4]	Eq.[3]	Eq.[4]
	DTAW * DRef	%TAW * DRef	DTAW * DRef	%TAW * DRef
1. Base Specification (Includes	0.053	0.210	-0.006	-0.086
Controls and Year Fixed Effects)	(0.006)	(0.032)	(0.028)	(0.094)
2. Add specific trend for TAW-user	0.112	0.452	-0.068	-0.179
plants	(0.008)	(0.037)	(0.027)	(0.098)
3. Adds specific trend for TAW-user	0.104	0.443	-0.068	-0.289
plants and plant Fixed Effects	(0.008)	(0.038)	(0.027)	(0.068)
Number of Observations	46153	46153	46153	46153

Specification	III. Change in Log Non-Agency Employment		IV. Change in Log Output	
	Eq.[3]	Eq.[4]	Eq.[3]	Eq.[4]
	DTAW * DRef	%TAW * DRef	DTAW * DRef	%TAW * DRef
1. Base Specification (Includes	0.089	0.424	-0.042	-0.144
Controls and Year Fixed Effects)	(0.030)	(0.123)	(0.033)	(0.104)
2. Add specific trend for TAW-user	0.124	0.811	-0.023	0.041
plants	(0.032)	(0.146)	(0.033)	(0.109)
3. Adds specific trend for TAW-user	0.089	0.664	-0.057	-0.104
plants and plant Fixed Effects	(0.024)	(0.120)	(0.019)	(0.056)
Number of Observations	46153	46153	46138	46138

Specification	V. Change in Log Value Added		VI. Change in Share Inventories	
	Eq.[3]	Eq.[4]	Eq.[3]	Eq.[4]
	DTAW * DRef	%TAW * DRef	DTAW * DRef	%TAW * DRef
1. Base Specification (Includes	-0.093	-0.328	0.026	0.051
Controls and Year Fixed Effects)	(0.039)	(0.136)	(0.012)	(0.031)
2. Add specific trend for TAW-user	0.067	0.272	0.009	0.031
plants	(0.044)	(0.160)	(0.016)	(0.045)
3. Adds specific trend for TAW-user	0.026	0.079	0.017	0.046
plants and plant Fixed Effects	(0.034)	(0.118)	(0.014)	(0.039)
Number of Observations	44384	44384	46153	46153

Source: Authors construction using manufacturing survey.
Note: Estimates from Equations [3] and [4]. Robust standard errors clustered at the plant level.

Table 4: Effects of the TAW Regulation by Intensity of Use

Outcome Variables	All Plants (1) Below Median DTAW * Dref	All Plants (2) Above Median DTAW * Dref	F-value & Prob > F (in parenthesis) (1) & (2) = 0	F-value & Prob > F (in parenthesis) (1) = (2)	TAW-user Plants (3) Above Median DTAW * Dref
Share Non-Agency Workers	0.029	0.190	87.960	98.110	0.162
	(0.006)	(0.015)	(0.000)	(0.000)	(0.016)
Log Total Employment	-0.050	-0.127	11.440	5.020	-0.076
	(0.022)	(0.029)	(0.000)	(0.025)	(0.033)
Log Non-Agency Employment	-0.022	0.217	15.060	27.640	0.240
	(0.023)	(0.041)	(0.000)	(0.000)	(0.044)
Log Output	-0.064	-0.049	4.930	0.220	0.011
	(0.023)	(0.027)	(0.007)	(0.643)	(0.033)
Log Value Added	0.010	0.044	0.370	0.270	0.030
	(0.041)	(0.052)	(0.694)	(0.600)	(0.062)
Share Inventories	0.009	0.025	0.810	0.690	0.015
	(0.014)	(0.020)	(0.444)	(0.406)	(0.019)

Source: Authors construction using manufacturing survey.
Note: Estimates from Equation [6]. Robust standard errors clustered at the plant level. Columns (1) and (2) pool all plants for estimation. Column (3) only considers plants that used TAW as of 2006. For all outcome variables, except value added and output, we have 46,153 plant-year observations in "All Plants" and 7,920 observations in "TAW-user Plants". For Log Output and Log Value Added we have, respectively 46,138 and 44,384 plant-year observations in "All Plants"; and 7,917 and 7,611 in "TAW-user Plants". Column "(1) & (2) = 0" shows the results from a test of jointly significance of the coefficients in columns (1) and (2). Column "(1) = (2)" shows a test for the linear hypothesis that the coefficients from columns (1) and (2) are equal to each other.

Table 5: Robustness - Alternative Specifications

	Specification	Share Non-Agency Workers	Log Total Employment	Log Non-Agency Employment	Log Output	Log Value Added	Share Inventories
(1)	Lagged Dependent Var (IV) & Plant Fixed Effect	0.088	-0.080	0.048	-0.027	0.017	0.005
		(0.009)	(0.016)	(0.019)	(0.015)	(0.031)	(0.011)
	Cragg-Donald Wald F	1504	1307	622	1630	6272	24000
	Kleibergen-Paap rk Wald F	191	261	112	353	2460	134
Observations		29532	36972	29478	36941	33387	36972
(2)	Plant Specific Trend & Plant Fixed Effect	0.075	-0.060	0.065	-0.016	0.053	0.010
		(0.008)	(0.017)	(0.020)	(0.015)	(0.033)	(0.016)
Observations		41313	41313	41292	41294	38805	41313

Source: Authors construction using manufacturing survey.
Note: Estimates in rows (1) and (2) correspond to Equations [7] and [8] respectively. Robust standard errors clustered at the plant level. For specification [7] we report both Cragg-Donald and Kleibergen-Paap rk Wald F-statistics for weak instruments.

Table 6: Robustness - Control Function and 2SLS.

Specification	Change in Share Non-Agency Workers		Change in Log Total Employment	
	DTAW * DRef	%TAW * DRef	DTAW * DRef	%TAW * DRef
1. Control Function	0.059	0.423	-0.089	-0.272
	(0.014)	(0.046)	(0.033)	(0.082)
Observations	43819	43819	43819	43819
2. Two-Stage LS	0.061	0.175	-0.086	-0.221
	(0.014)	(0.059)	(0.034)	(0.111)
Observations	45202	36980	45202	36980
Cragg-Donald Wald F	6868	8684	6867	8684
Kleibergen-Paap rk Wald F	400	136	399	136

Specification	Change in Log Non-Agency Employment		Change in Log Output	
	DTAW * DRef	%TAW * DRef	DTAW * DRef	%TAW * DRef
1. Control Function	0.028	0.789	-0.145	-0.102
	(0.043)	(0.147)	(0.037)	(0.070)
Observations	43819	43819	43804	43804
2. Two-Stage LS	0.036	0.283	-0.119	-0.291
	(0.043)	(0.226)	(0.038)	(0.110)
Observations	45202	36980	45187	36970
Cragg-Donald Wald F	6867	8685	6871	8682
Kleibergen-Paap rk Wald F	399	137	400	136

Specification	Change in Log Value Added		Change in Share Inventories	
	DTAW * DRef	%TAW * DRef	DTAW * DRef	%TAW * DRef
1. Control Function	-0.034	0.034	0.003	0.023
	(0.065)	(0.148)	(0.045)	(0.053)
Observations	42147	42147	43819	43819
2. Two-Stage LS	-0.039	0.109	-0.029	0.119
	(0.064)	(0.212)	(0.067)	(0.076)
Observations	43383	35559	45202	36980
Cragg-Donald Wald F	6772	8481	6868	8685
Kleibergen-Paap rk Wald F	398	134	400	137

Source: Authors construction using manufacturing survey.
Note: Estimates in rows (1) and (2) correspond to Control function approach as described by equation [9] and 2SLS, respectively. Robust standard errors clustered at the plant level. For 2SLS we report both Cragg-Donald and Kleibergen-Paap rk Wald F-statistics for weak instruments.

FIGURES AND TABLES - APPENDIX

Table A1: Evolution of each component of Eq. [A]

Table A1: Evolution of each component in Eq. [A].

	Share TAW	$\overline{ShTAW}_U$	$\bar{l}_U/\bar{l}_M$	ShN_U	*1+Cov-Term*
2001	0.07	0.21	1.84	0.18	1.04
2002	0.08	0.22	1.76	0.18	1.13
2003	0.09	0.23	1.76	0.19	1.13
2004	0.10	0.25	1.86	0.19	1.17
2005	0.12	0.26	1.98	0.19	1.20
2006	0.13	0.26	1.96	0.19	1.31
2007	0.12	0.25	2.12	0.18	1.32
2008	0.12	0.23	2.45	0.17	1.21
2009	0.12	0.24	2.61	0.16	1.19
2010	0.10	0.23	2.46	0.15	1.16
2011	0.10	0.23	2.60	0.15	1.08

Source: Authors construction using manufacturing survey.
Note: $\overline{ShTAW}_U$ represents the simple average of the share of TAW; $\frac{\bar{l}_U}{\bar{l}_M}$ is the average size of plants using TAW divided by the average size of all plants in manufacturing; ShNU is the ratio between the number of plants using TAW and all plants in manufacturing; and finally "Cov-Term" is the covariance between the share of TAW and the plant´s size conditioning on using TAW.

Table B1: Summary Statistics of the Data Set

	Observations	Mean	Std.Dev.	Min	Max
Plant-Year Observations (2001-2011)					
Total Employment (log)	53,846	3.48	1.2	-	8.66
Regular Employment (log)	53,846	3.42	1.18	-	8.18
Output (log)	53,829	13.24	1.88	6.15	22.2
Value Added (log)	51,760	12.11	1.89	2.28	21.93
Share of TAW	53,846	0.04	0.13	-	0.99
Total Employment (log change)	43,882	0	0.25	-1.5	1.44
Value Added (log change)	43,882	0	0.59	-3.33	3.02
SD Value Added (log change)	40250	0.49	0.38	0	4
SD Predicted Value Added (log change)	31670	0.06	0.03	0	0
Plant-Year Observations (1995-2011)					
Export Share	71,158	0.07	0.21	-	1
Import Share	74,045	0.08	0.18	-	1
Plant Observations					
Labor Share	15,766	0.24	0.15	-	1.2
Fuel Share	15,801	0.02	0.02	-	0.24
Electricity Share	15,774	0.02	0.02	-	0.22
Year Observations 1995 -2011					
Manuf.Wage (log)	17	4.3	0.17	4.07	4.57
Electricity Price (log)	17	3.79	0.34	3.27	4.31
Oil Price (log)	17	9.74	0.56	8.7	10.5
Real Exch.Rate (log)	17	6.14	0.18	5.78	6.43
Sector-Year Observations (1995-2011)					
Deflactor (log)	296	4.61	0.24	3.95	5.68

Source: Authors construction using manufacturing survey.
Note: The summary statistics for employment, output, value added, share of TAW and Inventory are for the period 2001-2011, for all other variables we report statistics for the period 1995-2011. Log change for employment and value added exclude 1% of extreme values. To compute the standard deviation, we also exclude 1% of extreme values. Input shares are constant at the plant level, input prices are at the manufacturing level, and the price deflator is at the sector level. All variables are in 2009 CLP$.

<u>Table C1: Log Change in Value Added and External Shock to the Plant</u>

	VA (log change)
Labor Share * Wage (log change)	-2.428
	(0.791)
Energy Sahre * Elect.Price (log char	-5.138
	(1.484)
Oil Sahre * Oil Price (log change)	-1.671
	(0.575)
Export Share	0.0214
	(0.017)
Export Share * RER (log change)	0.191
	(0.197)
Import Share	-0.0272
	(0.0186)
Import Share * RER (log change)	-0.0606
	(0.21)
Sector Price (log change)	0.229
	(0.0412)
IV Lag VA (log change)	0.0864
	(0.0162)
Observations	44002
Time and Sector FE	YES
R-squared	0.012

Source: Authors construction using manufacturing survey.
Note: Period 1997-2011. Robust standard errors clustered at sector-year level.

Table C2: Log Change in Value Added and TAW

	VA (log change)	VA (log change)	VA (log change)	Std.Dev. VA (log change)	SD(dlva) VA (log change)
Predict VA (log chage)	0.937	0.810	0.811		
	(0.057)	(0.217)	(0.216)		
Predict VA (log chage)		0.349			
x DTAW t-1		(0.167)			
Predict VA (log chage)			0.126		
x DTAW(<med) t-1			(0.217)		
Predict VA (log chage)			0.628		
x DTAW(>med) t-1			(0.234)		
DTAW t-1		0.007			0.027
		(0.011)			(0.005)
DTAW(<med) t-1			-.001		
			(0.017)		
DTAW(>med) t-1			.006		
			(0.014)		
SD(Predict dlva)				1.842	1.845
				(0.209)	(0.213)
Observations	33078	33078	33078	33606	32956
Time and Sector FE	No	YES	YES	YES	YES
R-squared	0.010	0.011	0.0106	0.0728	0.0745

Source: Authors construction using manufacturing survey.
Note: Period 2001-2011. Robust standard errors clustered at sector-year level.