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Investment in second-hand capital goods and energy intensity

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Abstract

This paper investigates the relationship between investment in new and second-hand capital goods and energy intensity. Using a panel dataset of about 4,500 Chilean firms for the period 2001-2007, we find that both types of investment help reducing energy intensity although second-hand machinery has a significantly lower effect. We conclude that, in order to reduce the energy intensity of the manufacturing sector, policies aiming at overcoming the constraints to new investment should be preferred to those that discourage investment in second-hand machinery (e.g. an import ban).

Keywords: energy intensity, investment, second-hand capital goods, Chile

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JEL: Q41, Q48, Q54

1 Introduction

Industrial energy efficiency plays a crucial role in achieving carbon emissions reduction targets. The manufacturing industry accounts for about 43% of the world's electricity consumption (IEA, 2013). Energy use and the pressure it puts on the environment are shaped by technology. Technology diffusion is therefore key to improving industrial energy efficiency worldwide. Technology is often embedded in capital. Despite the obvious benefits, however, brand new technologies might not be affordable by developing countries. Firms may thus delay the adoption of performance standards imposed on new machinery. Or they may adopt a performance standard that was imposed on another sector or in another country. New technology is costly and many firms continue to invest in old technologies, i.e. replacement capital-goods that do not incorporate state-of-the-art energy efficient technology, which is often referred to as the "energy paradox" (Jaffe and Stavins, 1994)[1] when there is a gap between the implemented technology and the most energy-efficient technology available. Second-hand capital goods could help reduce this gap if they allow achieving lower energy intensity at reasonable costs.

Closely related to this, trade in second-hand machinery has received little attention in the public debate when compared to the attention given to the international trade of environmentally-friendly technologies (e.g. Agenda 21) and the cross-border transport of harmful waste (e.g. the Basel Convention) (Janischweski et al., 2003). The role of second-hand machinery both in terms of competitiveness and environmental impact is unclear. The attitude of developing countries towards the import of second-hand capital goods is diverse and varies over time. Some emerging economies have undertaken, or are in the process of undertaking, measures against the import of second-hand capital goods. India, for example, has been discussing the ban of import of second hand plants and machinery. The ban has been advocated by arguments of competitiveness and higher energy efficiency. Brazil, Argentina, Pakistan and other countries in Asia and Latin America, impose import restrictions

[1] The paper identified several causes of this paradox, some are associated to potential market failures - information problems, principal/agent slippage, while others relate to unobserved costs: private information costs, high discount rates, and heterogeneity among potential adopters.

on second-hand machinery for safety and environmental reasons (Czaga and Fliess, 2004).

In this paper, we explore the impact of new versus second-hand capital goods on energy use by manufacturing firms. There is a trade-off between the benefits and the costs of using second-hand capital goods. On the one hand, second-hand capital goods are available at lower costs (Eisfeldt and Rampini, 2007), might provide a better match to the skills and labor abundance of developing countries than new technologies (Sen, 1962) and can potentially constitute a cheap but more energy efficient option to obsolete capital goods (Davis and Kahn, 2010). On the other hand, second-hand capital goods may require higher maintenance costs (Sen, 1962), are more energy intensive than new technologies, can provide a disincentive to the development of the domestic capital goods industry, and may have a shorter economic life. Whether the benefits prevail over the costs depends on several factors: the quality of the traded new and used goods, the quality of the domestic new and in-use capital goods and the changes in costs and competitiveness resulting from the capital good investments.

This paper focuses on Chile, one of the few countries that holds micro data on new and second-hand investment. Chile does not impose import restrictions on the international trade of used capital goods, other than vehicles, and the second-hand capital market is well-developed[2]. We use a comprehensive survey of Chilean firms, the Encuesta Nacional Industrial Annual (ENIA), that records information on the purchase of new and second-hand machinery for a panel of more than 4,500 firms, de facto a census of large firms, from 2001 to 2007.

To the best of our knowledge this is the first study that empirically assesses the impact of investment in second-hand machinery on energy intensity at the firm level. Most of the empirical literature in this field has focused on trade in second-hand capital goods and, in particular, on second-hand vehicles mainly because of the lack of suitable data on second-hand machinery and equipment at firm, sector or country level. Sen (1962) is one of the first to analyze the second-hand capital goods market by exploring the reasons behind the large transfers of second-hand capital goods from developed to less developed countries. More recently Navaretti et al. (2000) examined the

[2]However note that there is a 50% surcharge of the applicable tariff when importing second hand goods; if a capital good is imported for investment purposes than it may be exempt from VAT.

determinants of trade in used equipment with a focus on the US exports of metalworking machine tools. They find that the demand for second-hand machinery is higher for equipment requiring more sophisticated operating skills and that it is negatively related to the level of education in the country. Finally, very few studies consider the environmental impact of second-hand capital goods. Davis and Kahn (2010), for example, analyse the impact of eliminating trade barriers on second-hand vehicles between Mexico and the United States. They find that trade from the United States to Mexico reduces average vehicle emissions per mile in both countries since traded used vehicles are dirtier than the stock of vehicles in the United States but cleaner than the stock in Mexico. However, they also find that trade has increased total emissions because of low vehicle retirement rates in Mexico.

The paper proceeds as follows. Section 2 outlines a simple model of energy demand and details our empirical strategy; Section 3 discusses the data we use; Section 4 provides some summary statistics on the characteristics of firms investing in new and second hand machinery; Section 5 details our results; and Section 6 concludes.

2 A simple model of energy demand

The empirical analysis presented in this paper can be supported by a theoretical model that takes into account varying levels of energy intensity and vintage capital. Different models have emerged in the literature to incorporate the energy-intensity of capital into a firm decision making process. Most of these are models of the long-term relationship between energy intensity and the price of energy, which is usually found to be very unresponsive in the short-term. One of the earliest attempt can be found in the vintage capital model proposed by Atkeson and Kehoe (1999). The authors propose two models, one that considers a strong complementarity between capital and energy (putty-putty model) and another where different types of capital are combined with energy in fixed proportions (putty-clay model). Similarly, Mulder et al. (2003) adopt a vintage capital model to explain the low diffusion of new technology that is associated to complementaries between different technologies that lead to a taste for technological diversity. While the above models assume that capital is fully utilized, Wei (2003) adapts the model of Gilchrist and Williams (2000) to incorporate variations in capital utilization.

The model used here draws extensively on that presented in Linn (2008) who provides a vintage capital model to explain the differences in energy intensity between incumbents and entrants after a price shock. Our model, however, does not distinguish between entrants and incumbents and the capital stock and energy technology can be modified in each period. Each plant produces a homogeneous consumption good according to the following constant elasticity of substitution production function:

$$Y_{it} = A_{it}[\alpha_K K_{it}^{\rho} + \alpha_L L_{it}^{\rho} + \alpha_E (A_{it}^{E} E_{it})^{\rho}]^{1/\rho}, \tag{1}$$

where Y_{it} represents output of plant i at time t, A_{it} is total factor productivity, K_{it} is capital stock, L_{it} is labor input and E_{it} is energy consumption. A_{it}^{E} is the average energy-augmenting technology. Increases in A_{it}^{E} imply energy-saving technological changes. Although A_{it}^{E} could be seen as the aggregated level of energy-intensity obtained by averaging capital-specific level of energy intensity, the theoretical model does not model a plant choice over different types of capital given their energy intensity and vintage-specific productivity as done in Atkeson and Kehoe (1999). We assume that inputs are gross complements, i.e. $\rho < 0$, as this is a robust finding in the empirical literature (Carraro et al., 2009). Plants take output and input prices as given and maximize profits:

$$\pi_{it} = Y_{it} - p_k K_{it} + p_L L_{it} + p_E E_{it}, \tag{2}$$

given the above technological constraint. Energy intensity, defined as E_{it}/Y_{it}, is obtained in logarithmic form from the first order condition for E_{it}:

$$\ln(E_{it}/Y_{it}) = \frac{\rho}{1-\rho}\ln(A_{it}^{E}) + \frac{1}{\rho-1}\ln(p_E) + \mu_{it} \tag{3}$$

where the time-variant element $\mu_{it} = 1/(1-\rho)ln(\alpha_E) + \rho/(1-\rho)ln(A_{it})$ incorporates all the unobservable plant characteristics. Given the assumption of gross complementarity between inputs, an increase in energy-augmenting technology will decrease energy intensity since more energy saving reduces energy consumption for a given level of output. The impact of the energy price is also negative; the parameter represents the short-term price elasticity of energy demand.

2.1 Empirical specification

From the model proposed in the previous section it is possible to derive the estimating equation by adding a random disturbance term, v_{it} and a vector of controls X_{it}.

$$\ln(E_{it}/Y_{it}) = \alpha + \beta \ln(A^E_{it}) + \gamma \ln(p_E) + X_{it}\delta + \epsilon_{it}, \tag{4}$$

where $\epsilon_{it} = \mu_{it} + v_{it}$. The above specification assumes that the time variant component μ_{it} is uncorrelated with the other variables. This strong assumption will be discussed in the subsequent sections. Most of the unobserved heterogeneity correlated with the explanatory variables is control for by allowing the error term ϵ_{it} to include a plant-specific fixed effect b_i while common shocks that affect energy intensity of all plants in a particular sector or region and year are controlled for by including a full set of time-region and time-sector fixed effects.

There are several issues involved with the estimation of the above model, in particular, related to the measurement of the energy technology A^E_{it} and endogeneity. First, it is not possible to directly measure A^E_{it}. Nevertheless, it is possible to proxy changes in plant-level energy-augmenting technology by considering changes in capital that incorporate different energy technologies. We assume, for simplicity, that the energy-augmenting technological factor in equation 4 is the average of the energy characteristics, a, of the different types of capital, j, forming the capital stock of a plant weighted by the value of each type of capital, k:

$$A^E_{it} = \bar{A}^E_{it} = \frac{\sum_j^n a^E_j k_j}{\sum_j^n k_j}. \tag{5}$$

where a can also be understood as the inverse of the energy efficiency of each type of capital, i.e. the energy required to operate each type of capital. It is now possible to define changes in capital that would lead to an increase in A^E_{it}. Consider investment in one of the n types of capital:

$$\frac{\partial A^E_{it}}{\partial k_i} = \frac{1}{\sum_j^n k_j}(a^E_j - \bar{A}^E_{it}), \tag{6}$$

The investment will lead to a decrease in the overall energy intensity of the capital stock if the energy required to operate the new acquired machinery is lower than the average level per unit energy requirement of the existing capital stock. Although the empirical literature suggests that firms might adopt technology that do not incorporate state-of-the-art energy-saving technology, it is reasonable to expect that investment in new machinery and equipment would have a below-average level of energy intensity, decreasing the overall energy intensity of the capital stock. Ultimately, whether investment in second-hand machinery is energy-saving is an empirical question that is investigated below. The estimating equation can, therefore, be re-written in term of changes in energy intensity:

$$\Delta \ln(E_{it}/Y_{it}) = \alpha + \beta_n I_n + \beta_u I_u + \gamma \Delta \ln(p_E) + X_{it}\delta + b_i + t_t + \epsilon_{it}, \quad (7)$$

where I_n and I_u indicate investment in new and used machinery respectively. The major challenges in identifying the effect of investment on energy intensity are found in the presence of unobserved time-variant factors potentially correlated with both investment and energy intensity and the potential simultaneity between the two variables. Both issues are discussed in subsequent sections.

3 Data

We use the Chilean annual survey of manufacturing industries (Encuesta Nacional Industrial Annual, ENIA) which provides an unbalanced panel of large firms (more than 10 employees) for the period 2001 to 2007. The dataset includes on average 4,500 firms each year. The survey records standard information on output, employment, assets and the sector to which the firm belongs. It also records detailed information on energy inputs, including electricity, petrol and diesel, both in volume and value. More importantly, this is one of the few surveys that also provide information on investment in new and used machinery and durable equipment. Table 1 provides the descriptive statistics for the main variables of interest. All nominal variables were transformed into real values using appropriate deflators. Output was deflated using the sector level deflator provided by the Chilean National Statistics Office while the values of new and used machinery were deflated using the GDP deflator obtained as the weighted average of the sector-level deflators. The price of electricity reported in column 3 is computed at firm level; average prices show minor variations across sectors.

Table 1: Descriptive statistics

sector	(1) E/Y	(2) Energy/ Costs	(3) Price elec	(4) % used	(5) % new	(6) % exporter	(7) New/ capital	(8) Used/ capital
Food	2.7	1.8	58.2	14.9	62.9	24.7	6.9	0.6
Textile	3.4	2.1	56.4	25.6	58.3	25.9	7.7	1.3
Wearing apparel	1.5	1.0	57.4	18.1	51.3	12.9	4.1	1.2
Leather	2.6	1.6	55.0	19.9	51.4	23.6	4.6	2.7
Wood	4.4	2.9	57.1	24.2	64.7	27.6	8.9	1.4
Paper/pulp	3.7	2.3	53.1	25.0	68.9	35.8	8.2	1.1
Printing/publish	2.3	1.5	60.6	23.6	58.9	9.6	9.0	2.3
Chemical	5.1	4.0	52.6	18.5	77.8	41.6	6.7	0.4
Rubber/plastic	5.2	3.2	52.5	21.7	74.7	29.8	10.7	0.9
Non-metallic pro	3.6	2.3	53.6	20.6	60.3	12.3	6.1	0.6
Basic metals	9.0	4.4	48.8	17.4	67.9	43.2	7.1	1.1
Fabricated metal	2.2	1.4	58.6	19.9	60.5	19.3	5.8	1.0
Machinery/equip	2.6	1.8	59.2	15.5	57.5	19.6	6.9	1.0
Vehicles & Other	2.6	1.9	58.2	16.3	52.0	12.2	4.4	0.8
Furniture	2.2	1.5	58.1	16.7	56.7	15.0	9.5	1.2
Total	3.3	2.1	56.7	18.7	62.3	23.4	7.2	1.0

Energy costs comprise on average about 2% of total variable costs. They reach a peak of 4.4% in the basic metal sector. Most of the energy costs are due to electricity consumption while fuel consumption amounts on average only to 24% of total energy costs. Gas is used only by few plants and is not considered in the analysis below. On average about 18% of the plants in the sample have acquired used machinery at least once over the considered period. There are no major differences between sectors, the percentage of firms buying second-hand machinery varies from 26% in the textile sector to 15% in the food industry, the largest sector in the country. About 62% of the firms in the sample have purchased new machinery over the period; the highest percentage is found in the chemical sector. We also see that the share of firms purchasing new versus used equipment is significantly higher in all sectors; moreover, the value of new equipment purchased is markedly higher than the value of used equipment purchased across all sectors.

4 Who invests in new and second-hand machinery?

Before analyzing how investment in new and used machinery affects energy intensity, we explore the characteristics of firms investing in the two types of machinery[3]. First, we estimate a linear probability model where the dependent variable is binary and indicates whether the firm has invested in either new or used machinery. We consider a set of explanatory variables including the total number of employees and binary variables indicating whether the firm exports, is foreign owned and/or is financially constrained. Following Bergoeing Vela et al. (2010), we consider information on loan tax payments to identify unconstrained firms. In Chile, all financial transactions involving credit are subject to a tax (Actos Jurdicos or Timbres y Estampillas). Firms that report paying such a tax are considered constrained. In addition, we also include the ratio of dividends over assets as an additional measure of liquidity availability. Total factor productivity (TFP) is measured using the Levinsohn and Petrin (2003) methodology where total expenditure on materials is used to control for unobservables. To allow for differences in technologies across sectors, different production functions were estimated for each 2-digit sector.

The results are based on a cross section obtained by averaging the characteristics of each firm over the period under consideration. About 75% of the firms in the sample acquired either used or new machinery over the period. The results reported in the first column of Table 2 describe the characteristics of these firms conditioning on multiple variables simultaneously. Firms that acquired either new or second-hand machinery at least once in the period tend to be more capital intensive and are more likely to be exporters and foreign owned. Investors are also larger and less likely to be financially constrained.

In the second column we consider the fraction of used-capital expenditure over total-capital expenditure during the period. Exporters and foreign owned firms tend to spend a lower fraction of capital expenditure on used machinery and equipment, while financially constrained firms tend to invest more in second-hand machinery. This latter result is in line with the findings

[3]This analysis is conducted for the purpose of providing suggestive evidence about the differences between the two types of investors rather than understanding the magnitude of causal relationships.

Table 2: Characteristics of investors

	(1) Dummy: invest	(2) Used/total investment
Employees	0.271***	-0.083***
	(0.035)	(0.016)
Capital intensity	0.001**	-0.000
	(0.000)	(0.000)
Dummy: financially constrained	-0.238***	0.022**
	(0.011)	(0.009)
Dividends/Assets	-0.008	-0.001
	(0.006)	(0.010)
Dummy: exporter	0.158***	-0.016**
	(0.011)	(0.008)
TFP	0.000*	-0.000***
	(0.000)	(0.000)
Dummy: foreign	0.051***	-0.039***
	(0.018)	(0.013)
Region	Yes	Yes
Sector	Yes	Yes
Observations	6981	4868

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

of Eisfeldt and Rampini (2007). It is, however, worth pointing out that our indicator of financially constrained firms has some drawbacks. Because this variable might fail to capture those plants that do not demand credit because they can self-finance their investment, we also considered as non-financially constrained those firms that received some positive interests during the period. On the other hand, some firms classified as unconstrained may actually be credit rationed, receiving only partial funding but still being classified as unconstrained. Unfortunately, this is the best measure that can be obtained using the available information. Given these drawbacks, this result should be interpreted with caution.

5 Results

This section discusses the results of estimating equation 7. Table 3 reports the OLS and fixed effects estimates where energy intensity is computed as the annual consumption of electricity (in Kwh) over output. Investment in new and second-hand machinery is measured by a dummy indicating whether a firm purchased new or used machinery during the year (column 1, 3 and 4) and by the log value of both types of investment (column 2 and 5).

Table 3: The impact of investment in new and used machinery on energy intensity: electricity

Dependent variable: $\Delta\ln(E/y)$	OLS (1)	OLS (2)	FE (3)	FE (4)	FE (5)
Dummy: used	-0.013		-0.045**	-0.041*	
	(0.018)		(0.023)	(0.024)	
Dummy: new	-0.024**		-0.035**	-0.035**	
	(0.010)		(0.017)	(0.018)	
Log of value: used		-0.001			-0.004
		(0.002)			(0.003)
Log of value: new		-0.002**			-0.004*
		(0.001)			(0.002)
Δ price (firm level)			-0.411***		
			(0.050)		
Δ price (sector level)	-0.283***	-0.283***		-0.347***	-0.348***
	(0.095)	(0.095)		(0.067)	(0.067)
Log of hours worked	-0.006	-0.005			
	(0.005)	(0.005)			
Log of assets	0.005***	0.005***			
	(0.002)	(0.002)			
Skill ratio	-0.000	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Share: foreign ownership	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Dummy: exporter	-0.004	-0.003	-0.020	-0.028	-0.027
	(0.012)	(0.012)	(0.036)	(0.038)	(0.038)
Region-Year	Yes	Yes	Yes	Yes	Yes
Sector-Year	Yes	Yes	Yes	Yes	Yes
Observations	24422	24422	24465	24465	24465
Plants			6312	6312	6312

Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The cross-section results show that while investing in new machinery has a negative and significant impact on changes in (log) energy intensity, investing in used machinery does not affect energy intensity when considering both measures of investment. These results are likely to be biased by the presence of firm-level unobservables that are correlated with the decision to invest in new or used capital goods. The subsequent columns, therefore, include plant fixed effects which control for time-invariant unobserved heterogeneity. The results show that investment in new and used machinery reduces energy intensity. The effects are not statistically different from one another and indicate that purchasing machinery decreases the consumption of electricity over output by about 3.5 to 4.5%. A 10% increase in the value of the investment reduces energy intensity by 0.4%.

Table 4: Results for firms that undertook investment in both new and used capital goods

Dependent variable: $\Delta\ln(E/y)$	FE (1)	FE (2)
Dummy: used	-0.042*	
	(0.023)	
Dummy: new	-0.133***	
	(0.038)	
Log of value: used		-0.005*
		(0.002)
Log of value: new		-0.014***
		(0.004)
Δ price (sector level)	-0.417***	-0.417***
	(0.086)	(0.086)
Skill ratio	-0.001	-0.001
	(0.005)	(0.005)
Dummy: exporter	-0.078	-0.079
	(0.086)	(0.085)
Dummy: foreign owned	-0.157	-0.159
	(0.150)	(0.152)
Region-Year	Yes	Yes
Sector-Year	Yes	Yes
Observations	5418	5418
Plants	1165	1165

Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The results also show, as expected, that the price of electricity is negatively related to energy intensity. While the specification reported in column 3 considers firm-level prices, all the following specifications use sector-region average prices of electricity which are less likely to be endogenous[4]. A one

[4]Large energy consumers in Chile can buy energy directly from the producer or distributor at freely negotiated prices.

percent increase in the price of electricity is expected to reduce energy intensity by about 0.3%. This can be interpreted as a short-run price elasticity so that the reduction in energy intensity induced by a price change is expected to come from inputs reallocation and better energy management. No other variables have a significant effect once we control for firm-level fixed effects.

The results described so far have not addressed the possibility that firms investing in new capital goods might be substantially different from those investing in second-hand machinery with potential effects on the estimates. The results reported in Table 4 consider only firms that have invested in both new and used capital goods. The sample is reduced to about 1100 plants (15% of the sample). These results provide us with a better estimate of the differential impact of investment in new versus second hand machinery. With the sample thus restricted, the impact of investment in new machinery is significantly larger than that of second-hand machinery. While investment in new machinery decreases energy intensity by 13%, the effect is more than halved in the case of investment in second-hand machinery. Nevertheless, second-hand investment still significantly improves energy efficiency. Below we provide a set of additional specifications to explore the robustness of the results.

5.1 Robustness checks

The first set of specifications attempts to address two major sources of unobserved heterogeneity that could be correlated with energy intensity and investment. One possible concern refers to the possibility that while productivity shocks may induce investment, they could also be correlated with changes in energy intensity. Focusing again on the reduced sample, the first column of Table 5 controls for changes in total factor productivity (TFP). Total factor productivity should also account for management quality that could also affect both investment and energy intensity (Bloom et al. (2010)). The results as far as both investment in new and used machinery are concerned remain almost unchanged suggesting that unobserved differences in plant productivity over time do not cause significant bias to the coefficients. A second concern refers to the possibility that unobserved financial constraints might affect a firms ability to invest and, at the same time, induce a firm to reduce costs by saving on energy bills. The second column of Table 5 includes the indicator of financially constrained firms presented above. The results are again unaffected by this additional control. The same occurs when controlling for capital intensity (capital-labor ratio) in column 3. Results are similarly robust when considering the log value of investment.

Table 5: Additional robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Δln(E/y)	Δ ln(E/y)	Δln(E/y)	Δln(E/y)	Δln(E/costs)	Δ(Energy/y)
Dummy: used	-0.046*	-0.046*	-0.046*		-0.058**	-0.044*
	(0.026)	(0.025)	(0.026)		(0.024)	(0.025)
Dummy: new	-0.136***	-0.135***	-0.138***		-0.120***	-0.082***
	(0.032)	(0.032)	(0.032)		(0.033)	(0.029)
Δ price (sector level)	-0.425***	-0.425***	-0.425***	-0.482***	0.048	0.134
	(0.081)	(0.081)	(0.081)	(0.070)	(0.095)	(0.089)
Δ TFP	-0.195***	-0.195***	-0.189***	-0.195***	-0.042	-0.137**
	(0.066)	(0.065)	(0.065)	(0.075)	(0.052)	(0.057)
Dummy: fin. const.		-0.007				
		(0.041)				
Capital intensity			-0.000			
			(0.000)			
Log of used/capital				-0.008*		
				(0.004)		
Log of new/capital				-0.017***		
				(0.005)		
Region-Year	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5418	5418	5408	5352	5426	5272
Plants	1165	1165	1164	1162	1165	1155

Robust standard errors in parentheses. Regressions also include the dummy variables exporter and foreign owned and the ratio of skilled over total employees which have been omitted from the table. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In the remaining columns we explore alternative measures of investment and energy intensity. Column 4 considers the ratio of investment in used and new machinery over the total value of the capital stock at the beginning of the year (this latter information is provided in the ENIA survey) and show similar differentiated effects. Finally, the last two columns consider energy intensity in terms of electricity costs over total variable costs (column 5) and energy costs (including fuel and coal) over output (column 6).

One final concern is that, although investment decisions are most likely to be driven by productivity objectives, firms that have experienced an upward trend in energy intensity could potentially be investing in new or used machinery in order to improve their energy efficiency causing a simultaneity bias in the results. Including lagged values of investment does not seem to be a feasible solution since investment is likely to produce a large immediate one-off drop in energy intensity while minor effects are expected in the subsequent years. We therefore use instrumental variables to address this problem. The results are reported in Table 6. The first column considers the percentages of firms buying new and used machinery at the sector-region level as instruments for the two investment dummies. Column 2 reports the two stage least square estimates obtained employing two additional instruments: the average value of investment in new and used machinery at the sector-region level. The instrumental variable estimates are larger than the previously reported OLS estimates confirming the presence of a positive bias when simultaneity issues are not addressed. The last column treats the suggested instruments as "imperfect instruments" (IIV) relaxing an important assumption required for the identification of the instrumental variable estimations: instruments are allowed to correlate with the error term. Nevo and Rosen (2012) suggest that if the instrument is correlated with the error term in the same direction as the correlation between the endogenous variable and the error term (Assumption 3 in their framework) and the instrumental variable is less correlated with the error term than the endogenous variable (Assumption 4) then it is possible to derive analytic bounds for the estimated parameters.

In our estimations the endogenous investment variables are likely to be positively correlated with the error term and the same is expected for the percentage of firms investing in new and used machinery at the sector-region level. At the same time it is reasonable to expect that these latter two variables are less correlated with the error term that the two endogenous investment variables. Because the two instruments are positively correlated with the endogenous variables, the IIV will yield only one-sided bounds. Following Nevo and Rosen (2012) it is, however, possible to combine the available instruments in order to obtain an additional composite instrument that is negatively correlated with the endogenous variable. In particular, we subtract the percentage of firms investing in new machinery at the sector-region level (Z_2) from the average value of investment in new machinery at the sector-region level (Z_1) using the following formula: $Z_3 = \sigma_{z2}/(\sigma_{z1} + \sigma_{z2})Z_2 - \sigma_{z1}/(\sigma_{z1} + \sigma_{z2})Z_1$, where σ indicates the standard deviation of the two instruments. A similar differenced instrument was ob-

Table 6: Instrumental variable estimates

	(1) IV	(2) 2SLS	(3) IIV
Dummy: used	-0.186*	-0.195*	[-0.236, -0.186]
	(0.088)	(0.070)	(-0.512, 0.027)
Dummy: new	-0.422*	-0.461**	[-0.518, - 0.422]
	(0.059)	(0.032)	(-1.003, 0.015)
Δ price	-0.479***	-0.480***	[-0.482, - 0.479]
	(0.000)	(0.000)	(-0.703, - 0.257)
Region-Year	Yes	Yes	Yes
Sector-Year	Yes	Yes	Yes
Observations	5338	5338	5338
Firms	1086	1086	1230
F-statistic	47	48	35

Robust standard errors in parentheses.
Column 3 reports the 95% confidence interval.
* $p < 0.1$, $^{*}* \ p < 0.05$, $^{*} * * \ p < 0.01$

tained for used machinery[5]. Using assumption 3, we report the estimated upper and lower bounds for the coefficients of the relevant variables[6]. Although the 95% confidence intervals fall slightly above zero the upper bounds for both investment variables are well below zero. The confidence intervals of the coefficients of investment in used and new machinery do not overlap confirming that while both types of investment have a negative impact on energy intensity the effect of the latter is significantly larger. While these results confirm the presence of a downward bias in previous results, the instruments have several drawbacks. Therefore, we prefer our previous estimates with the caveat that they represent conservative estimates of the impact of investment on energy intensity.

[5]The percentages of firms investing in new and used machinery were found to be more partially correlated with the endogenous variable (0.21 for used, and 0.16 for new machinery) than the other instruments. We also tested that the following condition was satisfied for both differenced instruments: $\sigma_{\tilde{y}z_1}\rho_{\tilde{x}z_1} < 0 < \sigma_{\tilde{y}z_2}\rho_{\tilde{x}z_2}$ in Nevo and Rosen (2012).

[6]It might be possible to narrow the boundaries by also imposing Nevo and Rosen (2012)s assumption 4. In our setting, however, it was not possible to further narrow the boundaries, therefore, we consider column 4 as the narrowest available estimates.

6 Discussion and conclusion

In this paper, we estimate the impact of investment in new and second-hand capital goods on the energy intensity of firms in Chile. We find that investment of any kind significantly reduces energy intensity. Pertinently, we also find that investment in new capital goods is both significantly and substantially better for energy efficiency than is investment in second-hand capital goods.

There are important policy implications from these results. A policy that discourages second-hand investment (e.g. an import ban as proposed in India) could improve energy intensity if new investment replaces second-hand investment. However, investment in second hand machinery can also, on average, improve energy intensity despite being older, allowing financially constrained firms to reduce energy costs. A policy discouraging second-hand investment could therefore reduce overall investment and hence decelerate energy efficiency improvement. For example, a simple back-of-the-envelope calculation suggests that, assuming unchanged prices and output, overall the industrial sector could have saved 2% of the electricity costs over the period 2001 - 2007 if firms had replaced investment in second hand machinery with new machinery. On the other hand, if firms had undertaken no investment in second-hand machinery, total electricity cost would have been 1.2% higher. The net effect of a policy that discourage second-hand investment is, therefore, ambiguous and depends on the degree of substitutability between new and second-hand machinery.

Firms investing in second hand machinery are more likely to be financially constrained and are less likely to be exporters and foreign owned. Additionally ballpark estimates suggest that, although new capital goods are more expensive than second hand machinery, it takes on average the same amount of years (about 14) to fully recover the cost of both types of investment through cheaper electricity bills[7]. If the policy objective is to increase energy efficiency then this might suggest that policy should be aimed at overcoming the constraints to new investment (especially if this is also more likely to lead to improved competitiveness). By improving access to credit firms may be encouraged to purchase new over second hand machinery and, consequently, undertake larger loans, while their ability to repay should remain unchanged

[7]Using the subsample of firms considered in table 5, the average cost of a new investment is about 350 thousands Chilean pesos compared to 118 thousands for second hand investment. Annual average electricity costs are about 192 thousands Chilean pesos.

given the greater savings on electricity costs.

Of course a policy that encourages new investment (e.g., by improving access to capital markets) would reduce energy intensity but may raise energy use as economic activity expands. There is definitely scope for future research on these questions. We focus on Chile because it is one of the few countries with firm-level data on this question. Even so, no distinction is made between domestic and imported capital goods; and no information is available on whether investment adheres to national or foreign technical specifications. With more detailed data, further insights could be gleaned by studying both the demand and supply of second hand capital goods at both national and international level, as well as the incentives and constraints to investment in both new and second-hand goods.

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