(Indirect) Input Linkages*

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Advanced manufacturing firms differ from backward firms in various aspects. They adopt better management practices, invest in flexible machinery suited to small batch production and implement integrated computer systems that facilitate a reduction in inventories. They hire more educated production and non-production workers to handle modern equipment and interpret market trends. All these features render advanced firms more apt to respond to demand and supply shocks. As a result, their product scope is larger, and their products have higher quality and shorter life spans. But to fully accrue these benefits of added flexibility and quality, advanced firms' input providers must also deliver flexibility and quality—they must also adopt advanced technologies.[1]

This difference in the usage of inputs between advanced and backward firms leads to a magnification effect of technology adoption if production exhibits (internal or external) increasing returns to scale. As a subset of firms adopt newer technologies and managerial practices, they become more stringent in their input purchases and may prod their suppliers to also adopt newer technologies. With increasing returns to scale, the cost of these advanced-technology inputs decreases, which in turn, increases the incentives for other firms that use these same inputs to upgrade their own technology. Analogous spillovers hold for downstream sectors. Firms that adopt newer technologies increase the availability of better inputs and thereby lower their customers' cost of using newer technologies.

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[1]See Milgrom and Roberts (1990) for more details and empirical references.

In other words, the adoption of advanced technologies by a subset of firms may trigger broad improvements in a wide range of firms.[2]

This paper provides suggestive evidence for this magnification effect. Section 1 describes the data. Empirical regularities in section 2 suggest that advanced firms demand inputs from other advanced firms. Although these results are not new, they justify the selection of variables in section 3, where we provide evidence that firms that source inputs that are typically demanded by advanced firms are themselves more likely to adopt advanced technologies. This focus on firms that are only *indirectly* linked in the production chain, through a common input market, is novel. Section 4 concludes.

1 Data

We use the Colombian Annual Manufacturing Survey (AMS) of all manufacturing plants in Colombia with at least 10 employees.[3] Our results focus on 1988 but similar patterns hold for other years. For each plant, we observe total sales and measure a plant's import intensity as spending on imported materials divided by its total spending on materials. Workers are classified into managers, technicians and non-technical production workers. Our measure of skill intensity is the number of managers and technicians divided by the total number of employees. We use average wage per worker as additional information on a plant's skill level, under the assumption that firms observe skills better than us econometricians and pay higher wages for them. AMS is uniquely rich in recording quantities and values of all goods produced and of all materials used by 8-digit product categories.[4]

[2] As in Rodriguez-Clare (2007), increasing returns to scale must hold at the technology level, not at the industry level. Fieler, Eslava and Xu (2014) formalize this mechanism and embed it in a quantitative model of international trade. In the model, a firm's technology choice is interconnected with other changes within the firm and with other firms' technology choices through input linkages.

[3] AMS includes some plants with fewer employees but with large value of production. For multi-plant firms, we take characteristics of the plant as indicative of the firm to which they belong. About six percent of plants are from multi-plant firms, but we do not observe to which other plants they are linked.

[4] There are about 4,000 product categories that are roughly comparable to 6-digit HS codes.

2 Direct Input Linkages

We document the distinctive importing behavior of skill-intensive firms. The results complement previous work that shows that advanced firms source inputs from other advanced firms, strongly suggesting the connection between the technology choice of a firm and of its input providers.[5] While our results are not new, they justify the use of import intensity in section 3 below to construct a measure of relative demand for higher-technology inputs. We do not observe direct measures of technology level such as investments in better management practices, product and process innovation, information technology and R&D intensive equipment. Since it is well-known that these technological improvements strongly complement skilled labor, we follow the literature in interpreting skill intensity as proxies for technologies.[6] We also assume that imported inputs are more advanced than domestic inputs. Not only do advanced (foreign) firms self-select into exporting, but Colombia's main trading partners in 1988 were the United States and Europe.

Panel A on table 1 regresses an import dummy on skill intensity and separately on the log of average wage. Using only the subset of importing plants, panel B regresses import intensity on these two measures of skill intensity, separately. All coefficients are positive and significant, except for the coefficient of zero on wages in panel B. After controlling for size, skill-intensive plants are more likely to import their inputs. Conditional on importing, these plants are more import intensive. Again, these results indicate that advanced firms value advanced (foreign) inputs more than backward firms.

3 Indirect Input Linkages

Empirical strategy We provide suggestive evidence that firms that share a common input market have interconnected technology choices. Consider a positive technology

[5]See Goldberg et al (2010), Kugler and Verhoogen (2012), and Voigtlander (2014) for example. Regressions similar to ours appear Bernard, Jensen, Redding and Schott (2007).

[6]See Berman, Bound, Griliches (1998).

shock to the auto-maker Mazda. Section 2 suggests that the shock *directly* increases the technology of Mazda's input providers, say steel producers. But the magnification effect of inputs occurs only if, through internal or external economies of scale, the overall quality of steel produced in Colombia increases, thereby increasing the technology of other firms that consume steel—e.g., other auto-makers, producers of household appliances and of capital equipment. This spillover from Mazda's steel providers to other firms consuming steel is the *indirect effect*.

Ideally, to pin down this effect, we would observe exogenous variation in demand for advanced inputs across product categories stemming from a subset of firms and study the effect of this variation on other firms' technology choices. Information on imported inputs gives us an imperfect proxy for this ideal variation.[7] For each product category, we take all the firms that buy material inputs from that category and calculate the share of those purchases that are imported. For each plant p, we calculate the weighted average of these import shares across the product categories of plant p's inputs. Denote this measure with M_p. Based on table 1, our interpretation is that producers in categories with a high import intensity face a high demand for quality. Then, M_p captures the demand for higher quality in the categories where plant p sources its inputs. Using plant-level data, we run regressions of the form:

$$y_p = \beta_0 + \beta_1 \ln sales_p + \beta_2 imports_p + \beta_p M_p + \varepsilon_p \tag{1}$$

where β are coefficients to be estimated, y_p is either plant p's log of average wage per worker or skill intensity, $\ln sales_p$ is the log of sales, $imports_p$ is either a dummy for whether plant p is an importer or the plant's import intensity, M_p is as defined above, and ε_p is a stochastic error.[8]

[7] We focus on across-sector variation because we do not observe much time variation. Questions on imports and exports were removed from AMS during the period of Colombia's trade liberalization, concentrated in 1991. We have not attempted a diff-in-diffs approach to our specification.

[8] We control for log of sales because size can directly influence skill intensity due to managers' span of control (Garicano and Rossi-Hansberg (2006)).

Results Table 2 reports the results of regression (1) with skill intensity as the dependent variable. Panel A contains the full sample. In the odd-numbered columns, the positive and significant coefficients on import share and import dummies indicate that import-intensive firms are more skill intensive, as per table 1. But once the M_p variable is introduced in the even-numbered columns these coefficients on $imports_p$ all go to zero. That is, once we control for the type of inputs that the plant demands, through M_p, then the plant's import behavior has no effect on its skill intensity.

The coefficient on M_p is large and statistically significant in all specifications. For example in column 2, a 10% point increase in the import intensity of inputs typically demanded by a plant is associated with an increase in its skill intensity of 1.2% points. The coefficient decreases when we introduce fixed effects for the output sector of plant p in columns 5 through 8. This result probably arises either because the variation in the choice of input categories across firms within the same output sector is small, or because competing against advanced firms in the output market dampens the incentives to invest in advanced technologies. Our interpretation for the positive coefficient on M_p is as follows. Input providers in product categories with high import shares face a high demand for better products. To the extent that some of these input providers respond by upgrading their technologies, they increase the availability of better inputs, which in turn leads other firms that use these same inputs to upgrade their technologies.

Reverse causality is obviously also present. A technology shock (an increase in y_p) drives up the demand for better inputs and increases M_p. But the results do not change in panel B where we restrict the sample only to importers, only to non-importers, or only to plants that neither import nor export. Since non-importers by construction cannot increase M_p, reverse causality is unlikely to explain all the results. Panel B also partially addresses the concern that the results are driven purely out of self-selection of advanced firms into sectors that offer advanced inputs. If imported inputs directly increase the technology of importing plants, they give us a parallel to the ideal above of a technology shock in one subset of firms (importers) affecting another set of firms (non-importers) through a common input market. And if there is some randomness in the decision to import, the shock is imperfectly correlated with domestic factors influencing non-importers' technologies.

On table 3, we change the dependent variable to the log of average wage. Only two results change. First, the coefficients on M_p are zero in the regressions with sector fixed effects—probably for the reasons cited above. Second on panel B, the coefficient on M_p is larger for the sample of non-importers. This result makes sense under the input-magnification hypothesis. Importers should be less sensitive to the characteristics of domestic inputs because they already access high-technology inputs from abroad.[9] Overall, we view our results as complementary to previous work and indicative of the magnification effect of technology choices through input-output linkages.

4 Conclusion

We provide suggestive evidence that technological advancements in some firms increase the technology of other firms indirectly linked to them in the production chain. Because technological improvements go hand in hand with other changes within firms, spillovers in technology choices have repercussions in the labor market and in patterns of specialization. Relevant applications are numerous: These spillovers may amplify the effects of international trade on technology choices and on the demand for skilled workers. They may shape the process of diffusion of a new technology, and influence the incentive for innovators to develop skill-biased technical changes.

[9] This result holds in the estimated model in Fieler, Eslava and Xu (2014).

Table 1: Import patterns

A. Dependent variable: Import dummy		
skill intensity	0.044^{**}	
	(0.022)	
log(average wage)		0.035^{***}
		(0.013)
number of observations	7015	7014
R-squared	0.38	0.26
B. Dependent variable: Import intensity (importers only)		
skill intensity	0.119^{***}	
	(0.033)	
log(average wage)		-0.005
		(0.018)
number of observations	1714	1714
R-squared	0.294	0.122

All regressions include sector-fixed effects and the log of plant sales. Standard errors are in parenthesis. $^{***}p < 0.01$, $^{**}p < 0.05$

Table 2: Plant skill intensity and indirect import effects

Panel A: full sample

	Dependent variable: skill intensity							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log sales	0.0260***	0.0260***	0.0259***	0.0262***	0.0175***	0.0176***	0.0182***	0.0182***
	(0.00157)	(0.00156)	(0.00168)	(0.00167)	(0.00166)	(0.00166)	(0.00177)	(0.00177)
import share	0.112***	0.0250			0.0625***	0.0245		
	(0.0136)	(0.0174)			(0.0142)	(0.0171)		
import dummy			0.0374***	0.00439			0.0134**	0.000146
			(0.00637)	(0.00714)			(0.00665)	(0.00704)
Input's manufacturing-wide import penetration (*Mp*)		**0.122*** **		**0.132*** **		**0.0695*** **		**0.0841*** **
		(0.0155)		**(0.0136)**		**(0.0181)**		**(0.0159)**
Observations	7,013	6,986	7,015	6,988	7,013	6,986	7,015	6,988
R-squared	0.068	0.077	0.064	0.077	0.176	0.179	0.174	0.179
FE of the sector of the plant	NO	NO	NO	NO	YES	YES	YES	YES

Panel B: restricted samples

	Dependent variable: skill share							
	Only importers				Only non-importers		Purely domestic	
Plant's log sales	0.0221***	0.0219***	0.0217***	0.0210***	0.0288***	0.0181***	0.0291***	0.0171***
	(0.00259)	(0.00258)	(0.00268)	(0.00268)	(0.00215)	(0.00233)	(0.00227)	(0.00249)
import share	0.108***	0.0349	0.0665***	0.00479				
	(0.0175)	(0.0256)	(0.0185)	(0.0240)				
Input's manufacturing-wide import penetration (*Mp*)		**0.112*** **		**0.121*** **	**0.127*** **	**0.0433***	**0.128*** **	**0.0474** **
		(0.0290)		**(0.0301)**	**(0.0183)**	**(0.0234)**	**(0.0187)**	**(0.0239)**
Observations	1,714	1,714	1,714	1,714	5,272	5,272	4,988	4,988
R-squared	0.062	0.070	0.289	0.296	0.040	0.133	0.040	0.134
FE of the sector of the plant	NO	NO	YES	YES	NO	YES	NO	YES

This table presents regressions of skill shares on plant characteristics. Panel B restricts the sample to only importers, only non-importers, or only non-importers and non-exporters. For each plant, its input's manufacturing-wide input penetration (Mp) is the weighted average, over a plant's inputs, of the share of that input's consumption (at the aggregate level) that is imported.
Robust standard errors reported in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3: Plant wage and indirect import effects

Panel A: Full sample								
	Dependent variable: log average wage per worker							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log sales	0.219***	0.219***	0.214***	0.214***	0.210***	0.210***	0.209***	0.209***
	(0.00265)	(0.00263)	(0.00283)	(0.00281)	(0.00276)	(0.00276)	(0.00294)	(0.00294)
import share	0.169***	-0.000283			0.0656***	0.0402		
	(0.0230)	(0.0294)			(0.0236)	(0.0284)		
import dummy			0.0940***	0.0464***			0.0298***	0.0223*
			(0.0107)	(0.0120)			(0.0111)	(0.0117)
Input's manufacturing-wide import penetration (*Mp*)		**0.241*** **		**0.199*** **		**0.0473**		**0.0536** **
		(0.0262)		**(0.0230)**		**(0.0301)**		**(0.0264)**
Observations	7,012	6,985	7,014	6,987	7,012	6,985	7,014	6,987
R-squared	0.546	0.555	0.548	0.555	0.612	0.616	0.612	0.616
FE of the sector of the plant	NO	NO	NO	NO	YES	YES	YES	YES

Panel B: restricted samples								
	Dependent variable: log average wage per worker							
	Only importers				Only non-importers		Purely domestic	
Plant's log sales	0.231***	0.231***	0.230***	0.230***	0.205***	0.197***	0.205***	0.198***
	(0.00480)	(0.00479)	(0.00510)	(0.00511)	(0.00350)	(0.00367)	(0.00365)	(0.00386)
import share	0.0574*	-0.0187	-0.0104	-0.0202				
	(0.0323)	(0.0476)	(0.0352)	(0.0458)				
Input's manufacturing-wide import penetration (*Mp*)		**0.117** **		**0.0192**	**0.270*** **	**0.0265**	**0.259*** **	**0.0259**
		(0.0537)		**(0.0576)**	**(0.0299)**	**(0.0369)**	**(0.0300)**	**(0.0371)**
Observations	1,714	1,714	1,714	1,714	5,271	5,271	4,987	4,987
R-squared	0.576	0.577	0.660	0.660	0.397	0.491	0.393	0.490
FE of the sector of the plant	NO	NO	YES	YES	NO	YES	NO	YES

This table presents regressions of wages on plant characteristics. Panel B restricts the sample to only importers, only non-importers, or only non-importers and non-exporters. For each plant, its input's manufacturing-wide input penetration (Mp) is the weighted average, over a plant's inputs, of the share of that input's consumption (at the aggregate level) that is imported.

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

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