International outsourcing and innovation in clean technologies*

Antoine Dechezleprêtre[1], Damien Dussaux[1], David Hemous[2], and Mirabelle Mûuls[3]

[1] *Grantham Research Institute on Climate Change and the Environment, LSE*
[2] *University of Zurich*
[3] *Imperial College Business School*

January 2016 - Preliminary, please do not circulate.

Abstract

We examine the impact of low-cost imports on firms' propensity to engage in material-saving ('clean') innovation and product innovation using a dataset that combines firm-level international trade data with self-reported innovation data for around 9,000 French companies observed from 1998 to 2010. We find robust evidence that a higher share of imports from low wage countries significantly decreases firms' propensity to engage in 'clean' technologies but also drastically increases firms' propensity to develop new products. A one standard deviation increase in the import share of products from these countries decreases firms' propensity to engage in environmental innovation by up to 7 percentage points and increases firm's propensity to develop new products by up to 15 percentage points. This suggests that trade with low-cost countries have significantly reduced environmental innovation and considerably increased product innovation during the past 20 years.

Keywords: firm-level imports, environmental innovation, product innovation
JEL Classification: F18, Q56, D22, L11, C25

*We thank Scott Taylor, Farid Toubal, Ron Davies, participants at seminars in Stirling, LSE, Mannheim and Maynooth as well as UCD Trade Group for helpful comments and suggestions. The financial support of the Global Green Growth Institute, the Grantham Foundation for the Protection of the Environment, and the UK Economic and Social Research Council through the Centre for Climate Change Economics and Policy is gratefully acknowledged. This work is supported by a public grant overseen by the French National Research Agency (ANR) as part of the Investissements d'avenir program (reference : ANR-10-EQPX-17 Centre d'accès sécurisé aux donnés CASD). The CASD provides the micro data sets we use.

1 Introduction

From 1996 to 2011, the share of non-OECD countries' imports in OECD's total imports increased by 11 percentage points to reach 33%.[1] This important shift in the pattern of trade is a result of rising trade openness between developed and developing countries following the different GATT trade rounds. Trade in energy intensive goods, accounting for 50% of trade in all goods from non-OECD to OECD, is a major determinant of this general trend.

In this paper, we examine for the first time whether access to materials from low-cost countries reduces firms' incentives to develop clean technologies. This is an important question given the pressing challenges posed by climate change and other environmental issues. There are now empirical evidence that cross-country differences in environmental regulatory stringency led pollution intensive industries to relocate from stringent to lax countries (Ederington, Levinson, and Minier, 2005; Levinson and Taylor, 2008; Kellenberg, 2009; Kheder and Zugravu, 2012). This phenomenon, called pollution haven effect in the literature, reflects the failure of unilateral environmental policies to reduce worldwide levels of pollution in a globalized world.

Here, we focus more specifically on how trade itself could influence green innovation dynamics. This is important for example in the case of climate change. As green technologies contribute to abate future emissions of greenhouse gases, their timing is key: it determines the cumulative levels of greenhouse gas in the atmosphere and hence the risk of dangerous climate change.[2] Providing incentives to develop new clean technologies has become a focus of environmental policy. It is not surprising, then, that understanding the determinants of clean technological change is a lively research area, both on the theoretical (Acemoglu, Aghion, Bursztyn, and Hemous, 2012) and on the empirical side (Aghion, Dechezleprêtre, Hemous, Martin, and Reenen, 2012; Veugelers, 2012). There are now several empirical evidence that environmental regulations lead to cleaner innovation.[3] As well as free trade shapes production output worldwide, it may also play an important role in determining innovation output and direction.

They are different ways how trade openness could impact firms incentive to innovate. First, higher trade openness could stimulate innovation because domestic firms face potentially higher competition from foreign firms. Several studies provide empirical

[1] Authors calculation based on Cepii's BACI database.

[2] Timing is especially important as technologies may be path dependent that is it is easier to innovate in clean technologies if these technologies are already well developed. The cost to switch from dirty to clean technologies increases as the path of dirty technologies expends.

[3] Ghisetti and Pontoni (2015)'s meta-analysis shows that 78% of the models from the primary studies find that the environmental policy variable has a statistically significant effect on environmental innovation.

evidence that firms operating in an industry where the degree of competition is high tend to be more innovative (Blundell, Griffith, and Van Reenen, 1995; Geroski, 1995; Nickell, 1996; Aghion, Bloom, Blundell, Griffith, and Howitt, 2005; Aghion, Bechtold, Cassar, and Herz, 2014). Second, trade openness in the presence of asymmetric environmental regulations could relocate not only production but also innovation.

In countries with strict environmental policies, firms have more incentive to reduce their emissions of pollutants. Companies have two strategies to comply with the regulations. First, they can innovate in clean technologies. Second, they can offshore a pollution intensive part of their production to countries with lower production costs. This second option becomes more profitable as trade costs get lower. Offshoring firms may therefore reduce the incentives to innovation in clean technologies. At the same time, as offshoring decreases overall costs, it may increase the incentive of firms to develop new products or carry general innovations, since they will have access to a larger market.

The effectiveness of unilateral strict environmental innovation on net global green innovation may be undermined by international trade as it is the case for net CO2 emissions in a situation of carbon leakage. We can formulate several outcome resulting from the offshoring to low-cost countries under asymmetric environmental regulations. First, clean innovation is not induced anywhere and dirty innovations continue to prevail in both strict and lax countries. Second, clean innovation is induced in sourcing countries and not in the offshoring countries. We can coin this situation as a clean innovation leakage. Third, clean innovation is induced only in the offshoring countries and not in the sourcing countries. Finally, clean innovation is induced in both sourcing and offshoring countries. Which of these distinct outcome prevails is an empirical question.

In this paper, we provide the first part of the answer to this global issue by focusing only on the impact of offshoring to low-production cost countries on the propensity to innovate in clean technologies of firms located in countries having strict environmental regulations.[4] To investigate this question, we use theory to model jointly firms' trade and innovation behaviour. Our theoretical model predicts that trade with low-cost countries leads firms to undertake less material or energy saving innovations compared to other types of innovation activities. This is because firms can reduce their variable cost of production by importing cheap intermediate goods from low-cost countries. Doing so reduces their incentive to innovate in order to increase materials productivity and lower their production cost.[5]

[4]It is equally important to investigate the effect of offshoring on sourcing countries to measure the impact of asymmetric on net global clean innovation and long-run emission. However, it is not the focus of the present paper.

[5]Because they both require firms to pay a fixed cost, import and innovation can become, at some point, mutually exclusive strategies to reduce variable cost of production.

To test this prediction and quantify this effect, we combine self-reported innovation data from the Community Innovation Survey with detailed firm- and product-level trade data for a sample of nearly 9,000 French companies observed from 1998 to 2010. Firm-level data allows us to control for (observed) firm heterogeneity, in particular whether the firm is also an exporter, is big, and has high productivity. We use industry fixed effects to take unobserved differences between industries into account.

We use product classification information to identify imported goods that enter into the production of material-intensive products. These 'material' goods include for example metal products, pulp, and refined petroleum. Information on the country of origin of imports allows us to estimate the relative cost of inputs faced by companies. We complement this firm-level trade data with data on 'clean' innovation activities carried out specifically to reduce the use of these inputs.

We find strong evidence that a higher proportion of 'material' imports sourced from low production cost countries has a negative impact on firms' propensity to engage in 'clean' innovation but a positive impact on product innovation. This finding is stable across various definitions of what can be considered a low production cost country. The magnitude of the effect is large: at the sample mean, an increase in the import share of products from low wage countries in a firm's total imports by one standard deviation (a move from 5% to 20%) is predicted to decrease firms' propensity to engage in environmental innovation by 7 percentage points and predicted to increase firms' propensity to develop new innovation by 15 percentage points. To put this figure into perspective, one can observe that the share of US imports of intermediate goods coming from China and India has gone from 2.0% in 1990 to 9.5% in 2010. Thus, our results suggest that, ceteris paribus, trade with low-cost countries have significantly reduced environmental innovation and considerably increased product innovations during the past 20 years.[6]

Our focus on the two largest fast-growing developing economies, China and India, is motivated by three reasons. First, as illustrated above, these countries have played a growing role in providing companies in developed regions with cheaper intermediate goods in the last two decades, particularly in labour-intensive sectors. Second, the competition from these emerging economies has given rise to heated policy debates over the pertinence of introducing measures to protect domestic industries. A third, more data-driven reason is that the analysis showed that our results are unambiguously driven by China and India, although they are fully robust to considering other country groups such as non-OECD or low-wage countries.

This paper has important policy implications for the current debate on carbon 'leak-

[6]Evidence suggests that, on the other side, competition from Chinese imports may have stimulated technical change in Europe Bloom, Draca, and Reenen (2011). Therefore trade might affect both the rate and the direction of technological change.

age'. In a free-trade world, increased carbon prices following adoption of unilateral climate policies may generate a pollution-haven effect in other countries or regions, whereby foreign countries specialise in the production of carbon-intensive products in which they have a newly acquired competitive advantage and which they can subsequently export back to 'virtuous' countries. Environmental policies may thus fail to achieve their desired objective while destroying jobs in environmentally-friendly countries.[7] Our paper suggests that leakage may not only affect jobs and emissions in the short run. It also affects long-run emissions and competitiveness by reducing incentives for firms to conduct innovation in 'clean' technologies. This may provide further justification for policies to prevent leakage, such as border-tax adjustment.

Our paper relates to two strands of the literature. First, we build on the empirical literature on trade and technological change.[8] Previous studies have demonstrated that import competition, in particular from low-cost countries, has an influence on product innovation (Bernard, Jensen, and Schott (2006); Iacovone, Rauch, and Winters (2010); Lelarge and Nefussi (2013)). Bloom, Draca, and Reenen (2011) show that Chinese import competition has led to increases in R&D expenditures, patents and total factor productivity among European companies. Goldberg, Khandelwal, Pavcnik, and Topalova (2010) and Colantone and Crinó (2011) have shown that cheaper imported inputs boost firms' performance and lead to the introduction of new products.

However, few papers consider the empirical effect of firms' *own* imports on their innovative activity. Bøler, Moxnes, and Ulltveit-Moe (2015) examine the interdependence of R&D and intermediate inputs and their joint impact on firm's productivity. Bøler, Moxnes, and Ulltveit-Moe (2015) find that importing increases productivity, which frees up resources that can then be used to increase innovation activity. Thus, trade affects the rate of technological change. Dachs, Ebersberger, Kinkel, and Som (2014) find that offshoring firms will spend more in R&D activities and therefore produce more process innovation. To the best of our knowledge, there is no paper that looks at the empirical effect of firm's own import from *low production cost countries* on their innovation. In this paper, we show that importing from low wage countries may also affect not only the *scale* of technological change but also its *direction* by reducing incentives for environmentally-friendly innovation.

Second, our paper relates to the vast literature on the determinants of environmental innovation. Many studies have used patent data to measure clean innovation (Popp,

[7]Recent empirical papers show evidence of leakage, although this effect seems small (Levinson and Taylor (2008)). For example, Aldy and Pizer (2011) show that an increase in energy prices in the US following the introduction of a 15$/ton carbon tax would induce a domestic production decline of between 3 and 4 percent among energy-intensive sectors and a roughly 1 percent increase in imports.

[8]The theoretical literature on trade and technology is well developed and has been growing constantly since the seminal paper by Grossman and Helpman (1991).

2002; Brunnermeier and Cohen, 2003; Aghion, Dechezleprêtre, Hemous, Martin, and Reenen, 2012), but an equally large number of papers have instead used data from the Community Innovation Survey (Horbach, 2008; Frondel, Horbach, and Rennings, 2008; Rennings and Rammer, 2011; Rennings and Rexhäuser, 2010; Rexhäuser and Rammer, 2011; Horbach and Rennings, 2012; Leeuwen and Mohnen, 2013; Veugelers, 2012). Most of the recent literature has focused on the impact of environmental policy on innovation (see e.g. Newell, Jaffe, and Stavins (1999), Popp (2002), Brunnermeier and Cohen (2003) and Johnstone, Haščič, and Popp (2010)).[9] No study has yet looked at trade with low-cost countries as a determinant of 'clean' innovation.

The paper proceeds as follows. Section 2 develops the theoretical model used to analyse jointly firms' trade and green innovation behaviour. The empirical strategy is developed in Section 3. Section 4 describes our data set. We present the empirical results in Section 5. Some extensions and robustness tests are contained in Section 6. Section 7 concludes.

2 Model

In this section we present a very simple model to guide our intuition for the empirical investigation. We consider a two country economy where the two countries are Europe and China. Both countries are endowed with a given fixed mass of low-skill workers and Europe is endowed with a mass of high-skill workers. Europe admits a representative agent whose utility is given by

$$U^E = C_0^E + \frac{1}{\alpha}\left(\int_0^1 C_i^{\frac{\sigma-1}{\sigma}} di\right)^{\frac{\sigma}{\sigma-1}\alpha},$$

where C_0^E denotes the European consumption of a homogeneous good, and C_i the consumption of a differentiated good. China admits a representative agent with utility $U^C = C_0^C$, with C_0^C the Chinese consumption of the homogeneous good. The homogeneous good is chosen as the numeraire and traded internationally. It is produced in both countries with low-skill labour with productivity w in Europe and w^* in China ($w > w^*$), such that low-skill wages are w in Europe and w^* in China. The differentiated good is produced monopolistically in Europe according to the production function:

$$Y_i = A_i \left((B_i Q_i)^{\frac{\varepsilon-1}{\varepsilon}} + H_i^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}},$$

[9] See Ghisetti and Pontoni (2015)'s meta-analysis for a comprehensive list of publications on the determinants of environmental innovation

where A_i denotes the overall productivity of variety i's production, B_i is the materials productivity for variety i, Q_i denotes the quantity of "aggregate materials" used for the production of variety i and H_i denotes the mass of high-skill workers hired for the production of variety i. H_i may represent the quantity of headquarters services or more complex intermediate inputs that go in the production of variety i. The quantity of aggregate materials is given by a Cobb-Douglas aggregate of a the amount of materials $j \in (0,1)$:

$$\ln Q_i = \int_0^1 \ln q_{ji} dj,$$

where q_{ji} denotes the quantity of material j used in the production of variety i. Note that with the Cobb-Douglas structure, there is no loss of generality in assuming a general materials productivity B_i for variety i, a formulation with material-specific productivities b_{ij} would be equivalent. Materials are produced competitively with low-skill labour in Europe or in China at price w and w^* respectively.[10] However, importing material j from China involves a large investment and we assume that during the period under consideration, the producer of variety i can only import a share N_i^C of materials from China (see Vogel and Wagner (2010), Kasahara and Lapham (2008), Andersson, Lööf, and Johansson (2008) or Castellani, Serti, and Tomasi (2010)).

Moreover at the beginning of a period, the producer of variety i inherits a productivity vector (A_i^0, B_i^0). She can invest in R&D to increase the productivity of technology A by a factor $\left(1+\gamma_i^A\right)$ at a cost $\psi\left(\gamma_i^A\right)$ (in units of the homogeneous good), and similarly she can increase the productivity of technology B by a factor $\left(1+\gamma_i^B\right)$ at cost $\psi\left(\gamma_i^B\right)$. We assume that the cost function ψ is increasing and convex with $\psi(0) = \psi'(0) = 0$. The empirical analysis interprets productivity improvements as discrete, while here, for simplicity, we represent them as incremental. This is, however, without consequence: we can consider that if γ_i^A is larger, the firm is more likely to report an innovation of type A (and similarly for γ_i^B).

2.1 Resolution of the model

The producer of variety i faces an iso-elastic demand $C_i = P_i^{-\sigma}\overline{P}^{\sigma+\frac{1}{\alpha-1}}$where P_i is the price of variety i and $\overline{P} \equiv \left(\int P_i^{1-\sigma} di\right)^{\frac{1}{1-\sigma}}$ is the price index for differentiated goods. Maximization of profits imply that $P_i = \frac{\sigma}{\sigma-1}c_i$, where c_i is the cost of producing variety

[10] Note that the lower cost of materials in China could also result from laxer environmental regulations.

i. The cost of producing variety i is given by:

$$c_i = \frac{1}{A_i}\left(v^{1-\varepsilon} + \left(\frac{c_i^Q}{B_i}\right)^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}},$$

where c_i^Q is the cost of sourcing one unit of aggregate materials and v is the wage of high-skill workers. Note that the relative demand for high-skill workers over aggregate materials is given by

$$\frac{H_i}{Q_i} = (B_i)^{1-\varepsilon}\left(\frac{c_i^Q}{v}\right)^{\varepsilon},$$

which is increasing in B_i if $\varepsilon < 1$. Therefore, we focus on the case where $\varepsilon < 1$, so that an improvement in B_i can be interpreted as a materials-saving innovation, while an increase in A_i will be a general process innovation (or a product innovation, which can be interpreted as a new variety of higher quality).

Since materials are cheaper in China than in Europe, the producer of variety i imports a share N_i^C of its materials from China (and $N_i^E = 1 - N_i^C$ from Europe). We then get $c_i^Q = w^{1-N_i^C}(w^*)^{N_i^C}$. Therefore the cost of producing variety i is decreasing in the productivity levels A_i and B_i and it is decreasing in the share of materials that can be sourced from China N_i^C. Moreover, the ratio of expenditures on materials sourced from China over materials sourced from Europe is given by

$$\frac{w^* N_i^C q_i^C}{w N_i^E q_i^E} = \frac{N_i^C}{1 - N_i^C}, \tag{2.1}$$

where q_i^Z, $Z \in \{C, E\}$ indicates the quantity of materials j used in the production of variety i, when material j is sourced from country Z. Overall, we get that post-innovation profits are given by:

$$\Pi_i = \frac{\xi}{\sigma - 1} A_i^{\sigma-1}\left(v^{1-\varepsilon} + \left(\frac{w^{1-N_i^C}(w^*)^{N_i^C}}{B_i}\right)^{1-\varepsilon}\right)^{\frac{1-\sigma}{1-\varepsilon}},$$

where $\xi = \overline{P}^{\sigma+\frac{1}{\alpha-1}}\frac{(\sigma-1)^{\sigma}}{\sigma^{\sigma}}$, profits are increasing in A_i, B_i and N_i^C.

The innovation decision results then from:

$$\max_{\gamma_i^A, \gamma_i^B} \frac{\xi A_{i0}^{\sigma-1}\left(1+\gamma_i^A\right)^{\sigma-1}}{\sigma - 1}\left(v^{1-\varepsilon} + \left(\frac{w^{1-N_i^C}(w^*)^{N_i^C}}{B_{i0}\left(1+\gamma_i^B\right)}\right)^{1-\varepsilon}\right)^{\frac{1-\sigma}{1-\varepsilon}} - \psi\left(\gamma_i^A\right) - \psi\left(\gamma_i^B\right),$$

we assume that ψ is sufficiently convex that the problem is concave and admits a unique solution defined by the first order conditions with respect to γ_i^A and γ_i^B respectively:

$$\psi'\left(\gamma_i^A\right) = \frac{\xi A_i^{\sigma-1}}{\left(1+\gamma_i^A\right)} \left(v^{1-\varepsilon} + \left(\frac{w^{1-N_i^C}\left(w^*\right)^{N_i^C}}{B_i}\right)^{1-\varepsilon}\right)^{\frac{1-\sigma}{1-\varepsilon}}, \tag{2.2}$$

$$\psi'\left(\gamma_i^B\right) = \frac{\xi A_i^{\sigma-1}}{\left(1+\gamma_i^B\right)} \left(\frac{w^{1-N_i^C}\left(w^*\right)^{N_i^C}}{B_i}\right)^{(1-\varepsilon)} \left(v^{1-\varepsilon} + \left(\frac{w^{1-N_i^C}\left(w^*\right)^{N_i^C}}{B_i}\right)^{1-\varepsilon}\right)^{\frac{1-\sigma}{1-\varepsilon}-1}. \tag{2.3}$$

With ψ sufficiently convex, γ_i^A and γ_i^B are small, so that we can derive comparative statics ignoring that the right-hand side of the first order conditions depend on γ_i^A and γ_i^B. Following (2.2), the productivity increase in the level of general technology γ_i^A is increasing in the levels of productivities A_{i0}, B_{i0} and in the share of inputs sourced from China N_i^C. The intuition is the following: the lower the production costs already are, the bigger is the market share and therefore the more profitable an innovation is.

Similarly, γ_i^B is increasing in A_{i0}. Differentiating (2.3) with respect to N_i^C implies:

$$\psi''\left(\gamma_i^B\right) \frac{\partial \gamma_i^B}{\partial N_i^C} \approx \frac{\psi'\left(\gamma_i^B\right) \ln\left(\frac{w}{w^*}\right)}{\left(\left(\frac{vB_i}{c_i^Q}\right)^{1-\varepsilon}+1\right)} \left((\sigma-1) - (1-\varepsilon)\left(\frac{vB_i}{c_i^Q}\right)^{1-\varepsilon}\right). \tag{2.4}$$

The first term represents a scale effect which captures the same intuition as in the case of γ_i^A: if the share of materials sourced from China is greater, the market share is larger and productivity improvements are more beneficial. The relative importance of that effect increases is higher when the elasticity of substitution across varieties is larger, as then cheaper varieties get a larger share of the market. The second term represents a substitution effect, which is negative under our assumption that $\varepsilon < 1$—so that high-skill workers are more complement to materials than materials are to each other. In this case, when materials become cheaper, they represent a lower fraction of production costs, so that innovating to reduce the cost of one effective unit of aggregate material becomes less interesting. That effect is relatively more important when ε is small, so that high-skill workers and materials are very complement, and when vB_{i0}/c_i^Q is large so that materials already represent a small share of production costs. Therefore a larger share of inputs sourced from China may lead to a decrease in innovation aiming at reducing the costs of materials, all the more that materials already represent a small fraction of costs. Note that the impact of a higher initial productivity for aggregate materials B_{i0} is similarly ambiguous.

Yet, taking the ratio of (2.3) with (2.2) gives:

$$\frac{\left(1+\gamma_i^B\right)\psi'\left(\gamma_i^B\right)}{\left(1+\gamma_i^A\right)\psi'\left(\gamma_i^A\right)} = \left(\left(\left(\frac{w^*}{w}\right)^{N_i^C}\frac{w}{vB_i}\right)^{\varepsilon-1}+1\right)^{-1}, \tag{2.5}$$

which shows that, unambiguously, innovation efforts are *redirected* from improving the productivity of materials to general innovation when the share of materials sourced from China increases.

2.2 Empirical prediction

The empirical investigation focuses on this last equation. In practice, however, we do not observe N_i^C but the share of imports coming from China and India, that is we observe $dirty\_share = \frac{w^* N_i^C q_i^C}{w\left(N_i^E - N_i^F\right)q_i^E}$, where N_i^F denotes the share of materials sourced from France. Using (2.1), we get:

$$\frac{N_i^C}{1-N_i^C} = \left(1-\frac{N_i^F}{N_i^E}\right) dirty\_share.$$

Under the assumption that firms which source a large share of their materials from China and India do not also source a large share of their inputs from France (at the expense of other developed economies), then *dirty_share* is a good proxy for N_i^C.[11] Furthermore, energy could be understood as one of the "materials" q_{ij}, so that innovations which reduce energy use per output can be embedded in increases in B_i. Alternatively if some of the materials q_{ij} are produced in-house, energy efficiency improvements amount to an improvement in this material productivity b_{ij}, and as explained above, the model with a single B_i index is equivalent to one with a continuum of b_{ij}.

In our empirical analysis, we look at the introduction of new products and services. Insofar as a new product aims either at increasing demand by adding a new variety or improving the quality of the existing product, or reducing overall costs, this type of innovation corresponds to an increase in A_i in our model. Therefore, equation (2.5) then delivers the following prediction:

Prediction *When a firm increases its share of dirty inputs sourced from China or India, its innovation effort will be relocated from materials and energy saving innovations towards an increase in the range of products or services.*

It is important to underline that in principle the causality between import strategy and innovation could go both ways (which is one of the reason our empirical strategy

[11] This is a reasonable assumption: if anything, firms which source inputs from China and India are more likely to be already more involved in international markets.

will rely on instrumental variables). To show this, assume that sourcing a share N_i^C of materials from China involves a fixed cost $f\left(N_i^C\right)$, with f increasing and convex. Then a firm will choose the share N_i^C of materials to be sourced from China as the solution to:

$$\max_{N_i^C} \frac{\xi A_i^{\sigma-1}}{\sigma-1}\left(v^{1-\varepsilon}+\left(\frac{w^{1-N_i^C}\left(w^*\right)^{N_i^C}}{B_i}\right)^{1-\varepsilon}\right)^{\frac{1-\sigma}{1-\varepsilon}}-f\left(N_i^C\right).$$

If f is sufficiently convex and satisfies Inada-type conditions, the problem will have a single interior solution, which satisfies:

$$f'\left(N_i^C\right)=\xi \ln\left(\frac{w}{w^*}\right) A_i^{\sigma-1}\left(\frac{w^{1-N_i^C}\left(w^*\right)^{N_i^C}}{B_i}\right)^{1-\varepsilon}\left(v^{1-\varepsilon}+\left(\frac{w^{1-N_i^C}\left(w^*\right)^{N_i^C}}{B_i}\right)^{1-\varepsilon}\right)^{\frac{1-\sigma}{1-\varepsilon}-1}.$$

N_i^C is increasing in A_i: the larger is the level of general productivity the more materials are sourced from China, which is due to a scale effect. The impact of a higher aggregate material productivity on the share of materials sourced from China exactly mirrors the analysis of the reverse relation, there is a scale effect which pushes towards more outsourcing from China, and a substitution effect which pushes towards less, the scale effect dominates when (2.4) is positive.

3 Empirical Strategy

3.1 Probit model

In this paper we empirically test the intuition about the direction of innovation developed above. In the theory section, we assumed that innovation was a continuous process for clarity of exposition. However, what we actually observe is a discrete intensity of material or energy saving innovation and product innovation.[12] In the community innovation survey, each firm is asked to qualify the importance of different objectives of their innovation activities. For each objective, firms choose among four possible answers: 'not relevant', 'low importance', 'moderate importance', and 'high importance'. We are interested in two of these objectives: 'Reduce material and energy consumption per unit of output' and 'Increase range of goods or services'.[13] We define our dependent variables as binary

[12]It is easy, however, to replace the continuous innovation process in the theory section by a probabilistic process, or even simpler, to consider that firms actually improves productivity continuously and self-report that it belongs in the upper category only when the improvements are large enough.

[13]Details available in Section 4 or table 6 in Appendix 7

variables equal to 1 when the objective is of moderate or high importance and zero otherwise. Accordingly, our empirical method uses a Probit model to estimate firm's clean innovation and product innovation intensity at period p conditional on some covariates. More specifically, we estimate:

$$Pr\left(Innov_{ip}^{\mathcal{O}} = 1\right) = \Phi\left(\alpha ImportShare_{ip} + \beta X_{ip} + \delta_j + \lambda_p + \eta_r + \epsilon_{ip}\right) \tag{3.1}$$

where $Innov_{ip}^{\mathcal{O}}$ is either the dummy variable defined above for 'material saving' innovation denoted $Innov_{ip}^{\mathcal{M}}$ or the dummy variable for 'product' innovation denoted $Innov_{ip}^{\mathcal{P}}$ for firm i at the period p. Φ is the cumulative normal distribution.[14]

Our main variable of interest $ImportShare$ is the share of imports from low production cost countries in total imports of the firm, which proxies for the average cost of inputs faced by companies.[15] In our baseline, low production countries are countries with a real GDP per capita that is lower or equal to 25% of France's real GDP per capita. We check in Section 6 that our results are robust to using various country groups. To be consistent with our theoretical model, we restrict the imports to 'material' goods when estimating the propensity to innovate in material saving technologies $Innov_{ip}^{\mathcal{M}}$.[16] However, there is no restriction on the type of good when estimating the product innovation equation $Innov_{ip}^{\mathcal{P}}$. Note that we do not have information on total input consumption, but only on total imports by companies. This feature of the data is an advantage since importing firms might differ systematically from non-importing firms. In particular, firms that do not import at all might have more financial capabilities available to pay for the fixed cost of innovation.

We include a number of firm level controls X that include firm size, group status, industry concentration, and its average wage paid to employees. We also include a comprehensive set δ_j of industry dummies of the 3-digits NACE classification, a comprehensive set λ_p of period dummies, and a comprehensive set η_r of region dummies. Section 4 provides greater detail on the data and the variables used in the estimations.

[14] We do not estimate an Ordered-Probit model since there are 4 ranked discrete choices per kinds of innovation for two reasons. First, as we will use an instrumental variable strategy, using a Probit model allows obtaining reliable F-statistics of the first stage regression. Second, the magnitudes of the effect estimated has clearer implication with a Probit model. In section 6.4 we use an Ordered Probit model to check the robustness of this methodological choice.

[15] As explained in the section 3.2 we do not use directly the average input prices paid by firmsbecause of obvious data constraint. Instead, we can reasonably assume that average input prices are negatively correlated with the share of inputs sourced from low production cost countries.

[16] See section 4.2 for the definition of 'material' products.

3.2 Endogeneity issues

The main issues we face in our empirical investigation is the endogeneity of our main independent variable. We are primary concerned with potential measurement errors in the share of imports from low production cost countries. In our theoretical model, the average input prices paid by firms is what causes change in innovation outcome. However, we do not have data on input prices for all companies in our sample. Instead, we use the share of imports from low production cost that is negatively correlated with average input prices. Our proxy is imperfect since it does not capture domestic inputs which is what theoretically determines innovation. Consequently, we have a structural measurement error in our main independent variable. This produces an attenuation bias that reduces estimates towards zero.

Omitted variables in model (3.1) that causes innovation as well as the share of imports from low production cost countries are also a source of endogeneity.[17] We identify two main omitted variables: financial capacity and ownership. First, firm's financial capacity is likely correlated positively with both innovation output and import from low production cost countries. Firm with high financial capabilities can spend more in R&D to innovate and can also pay the fixed cost of importing.[18] For French firms, these fixed cost are much higher when importing from China or India than when importing from any EU member state. Therefore, we expect financial capabilities to be positively correlated with the share of imports from low production cost countries.

A second potential omitted variable is whether the firm is owned by a foreign firm, in particular to a firm operating in the low production cost countries. A French firm that is owned by a Chinese firm will face a lower fixed cost of importing from China. Therefore, foreign ownership is expected to be positively correlated with the share of imports from low production cost countries. Additionally, a firm that is foreign owned will be more exposed to technology transfers from foreign countries that contribute to the innovation process. Because of these positive correlations, omitting firm's financial capabilities or foreign affiliation results in an upward bias.

We address these endogeneity issues using an instrumental variable strategy. We use changes in real exchange rates from France to country of origin of imports as a source of exogenous variation. Our instrumental variable aims to capture the aggregate change in real exchange rate for low production cost countries relative to all countries. More

[17] Innovation and importing strategies are caused by common factors which generates reverse causality.

[18] Recent works such as Halpern, Koren, and Szeidl (2015) find that fixed costs of importing increase in the number of imported products.

specifically, our instrumental variable RER_{ip} is calculated as follows:

$$RER_{ip} = \frac{\sum_{c \in \mathcal{L}, t \in p} w^{\mathcal{G}}_{ic,p-1} \dfrac{RER_{ct}}{RER_{c0}}}{\sum_{c, t \in p} w^{\mathcal{G}}_{ic,p-1} \dfrac{RER_{ct}}{RER_{c0}}} \tag{3.2}$$

where RER_{ct} denotes Real Exchange Rate from country c's currency to Euro at year t, $\mathcal{L}$ denotes the set of low-cost countries, $\mathcal{G}$ is the set of goods which is the set of material goods $\mathcal{M}$ when the dependent variable is material saving innovation or the set of all goods $\mathcal{A}$ when the dependent variable is products innovation.

Our instrument is the ratio between a weighted average of real exchange rate variation from a base year 0 for low production cost countries and a weighted average of real exchange rate change for all countries. If the real exchange rates from a foreign currency to Euro increase more for low production cost countries than for high production cost countries, then we expect the share of imports from low production cost countries to increase. Here RER_{ct} is defined such that one Euro can buy RER_{ct} foreign currency. When RER_{ct} increases, French firms can buy a higher amount of foreign goods with euros so that M_{icgt} increases. Therefore, we expect our instrumental variable to be positively correlated with our endogenous variable.

In equation (3.2) each sourcing country is weighted according to its importance in the firms total imports. For instance, if China represents 10% of total imports and India represents 2% of the firm total imports, a 10% change in Real Exchange Rate from Yuan to Euro will have a larger impact on the firm imports than a 10% change in Real Exchange Rate from Indian rupee to Euro. To take into account the relative importance of the sourcing countries, we compute for each bundle of firm i and sourcing countries c a specific weights $w^{\mathcal{G}}_{ic,p-1}$ used in our instrumental variable. These weights are calculated as follows

$$w^{\mathcal{G}}_{ic,p-1} = \frac{\sum_{g \in \mathcal{G}, t \in p-1} M_{icgt}}{\sum_{g \in \mathcal{G}, t \in p-1, c} M_{icgt}} \tag{3.3}$$

where M_{icgt} is the import of firm i of product g from country c at year t. The weights are calculated using firm's imports of the previous period $p-1$ so that our instrumental variable does not influence firm innovation at period p. Eventually, we assume that our instrument variable does not influence firm level innovation conditional on our control variables.

4 Data

Our data are a composite of three main data sets on French manufacturing firms. Data on environmental innovation come from 6 waves of the Community Innovation Survey. International trade data are provided by the French Customs authorities. Finally, firm-level information (such as turnover, capital, etc.) comes from the Ficus database of Insee. Below we describe each of the data sets in turn.

4.1 Innovation data

We use the CIS data to construct our set of dependent variables. The CIS data set contains survey data and covers only a fraction of the population of French firms present in our other data sets described below. The CIS asks French firms about their activity in terms of product and process innovation, R&D, cooperative behaviour in research and innovation alliances over the last three years before the survey. The waves covering the years 1994 to 2010 include a set of questions on environmental innovation and product innovation.[19] For each wave, the survey asks how important were innovations that reduce either the use of material or energy per unit of output in firm's decision to innovate during the last three years. Similarly, the survey asks how important where innovations that increase the range of products of the firms. Firms have four exclusive choices to reply: 'not relevant', 'low importance', 'medium importance', and 'high importance'.[20] The survey questions related to environmental innovation and product innovation are presented in the Appendix.

Table 1: Importance of material saving innovation and product innovation

Importance	**Not relevant**	**Low**	**Medium**	**High**
Material saving	19%	24%	31%	26%
New product	9%	6%	20%	65%

Shares calculated for 2,217 firms in period 2008-2010

Table 1 provides the share of each reply for material saving innovations and for product innovations in period 2008-2010 that yields the highest number of observation. As the firm composition of the sample change over time, it is not possible to comment about

[19]Note that there was no survey for 1996-1998 and 2000-2002.

[20]The survey question about environmental innovations takes a different form for the 2006-2008 wave. Instead of being asked how important are green technologies in their innovation strategy, firm were asked whether they had introduced a material saving innovation and whether they had introduced an energy saving innovation. The dependent variable equals to 1 if the firms introduced both innovations and zero otherwise. When estimating our model without the 2006-2008 wave, we get very similar result.

the evolution of these shares. However, we can make two remarks. First, firms declare on average that increasing the range of the products they sell to be more important than reducing the material or energy consumption per unit of output. This is consistent with expectations. Second, the importance of material saving innovation is almost uniformly distributed across each categories and this holds for every period. This means that the survey is somewhat successful at ranking firms and that we will have good variation in the variable of interest.[21]

4.2 International trade data

International trade data are collected by the French customs authorities. The data include firm-level information on imported products, including information on the country of origin. International trade data contain information on all French firms involved in exporting or importing activities and reporting their transactions to the customs authorities.This data set includes information on the country of origin of imported products and on the country of destination of exported products, value and quantity (in tonnes), product classification at CN8 level (8-digit level of Combined Nomenclature classification) and, where available, corresponding Prodcom code.The international trade data are available for a period of 1994-2010.

To construct our main variable of interest we use information on product codes, transaction value and origin country of imports. Our theoretical model provides predictions about 'material' goods. They are intermediate goods that are not 'complex'. For instance, they include primary plastic, crude steel, wood pulp, etc. [22] 'Material' goods exclude 'complex' intermediate goods such as computer motherboards or bodies for motor-vehicles that are used to produce final goods. We use the Global Industry Classification Standard (GICS) to classify CN8 goods into material goods or not. The GICS defines a 'material' sector that contains several manufacturing industries: chemicals, construction materials, glass, paper, forest products and related packaging products, metals (including producers of steel), minerals and mining.[23] The first two digits of the CN8 matches with the definition of the material sector of the GICS. However, plastic products are absent from the GICS definition. As they are as material as steel or paper products, we decide to add plastics products found in the trade CN8 in the material category. Selected CN8 codes for material can be found in table 4 in the Appendix.

[21]We would have been worried about the quality of the data if 90% of the firms were concentrated in only two score categories.

[22]We do not mean that these products are not sophisticated.

[23]The Global Industry Classification Standard can be found here: https://www.msci.com/resources/pdfs/GICSSectorDefinitions.pdf

We then identify certain regions of the world with low wage in the manufacturing sector. We focus on countries with real GDP per capita lower than 25% of France's but show robustness of our results to considering other definition of low wage countries. When our dependent variable is material saving innovation, we combine import origin and product information to identify 'material' products from 'low-cost' origins to construct our main explanatory variable: a firm's share of 'material' imports from Southern countries in its total 'material' imports. This variable is defined as the value of 'material' products imported from the low production cost countries during the first two years of a CIS period divided by the value of total 'material' imports of a firm in these same two years.[24] The main independent variable is similar when the dependent variable is product innovation except that we do not restrict the goods to be material.

4.3 Financial data and estimation sample

The financial data on manufacturing firms come from two main data set. The first is the Unified and Comprehensive File of SUSE (FICUS) database. FICUS is based on an annual fiscal census of manufacturing, mining and utilities firms called Unified Corporate Statistics System (SUSE). SUSE is conducted by the French Ministry for the Economy and Finance at the firm level.[25] SUSE covers all firms that are under the (industrial and commercial benefit) BIC tax system or under the (non commercial benefit) BNC tax system. Simply, SUSE covers all firms that send their tax return to the French Ministry for the Economy and Finance.

The FICUS data set on manufacturing firms provides an unbalanced panel covering over 3 millions firms for a maximum of 14 years for the 1994-2007 period. Three kinds of variables are available. First, there are firm information such as primary industry classification (at 2-3 digits NACE level), head office address, employment (measured as total employed), date of creation, etcetera. Second there are profit and loss account (income statement) variables such as total turnover, export, total labour costs, total gross earnings, etcetera.Finally, there are balance sheets variables such as the stock of capital, debt, etcetera.

The second data set for financial data is the Annual business survey (EAE) on the manufacturing industry.[26] In contrast with SUSE, it is not a census but a statistical

[24] We take only the first two years of each period instead of three to avoid having overlapping observations. We show below that it does not affect our result.

[25] For more information on the other data set described here, see the website of the French National Institute of Statistics and Economic Studies at http://www.insee.fr/en/methodes/default.asp?page=sources/ope-enq-suse.htm.

[26] For more information on this and other data sets described here, see the

source. Firms having at least 30 employees or a annual turnover of at least 5 millions euros must reply to the survey. However, the other manufacturing firms are randomly sampled. The EAE data set on manufacturing firms provides an unbalanced panel covering on average 21,000 firms accounting for 2,9 millions of workers. The EAE data set contains almost the same variables as FICUS. For the period 1994-2007, we merge EAE and FICUS and keep data of the latter when the data for a firm is available in both data sets because FICUS is a census and thus considered as more reliable. To obtain data for 2008, 2009, and 2010 we use the FARE file, the data set that replaced both EAE and FICUS from 2008.[27]

We use the fiscal data set composed by FICUS, EAE, and FARE to control for observed firm-level characteristics. Firstly, we account for firms' productivity in two ways. We control for firm's labour productivity, measured as a total turnover per employee per firm-year. To the labour productivity measure we add a control for capital which is the book-value of capital net of depreciations. Secondly, since larger firms may have more resources available to engage in innovative activities, we include total employment in order to control for firm size. As for the variable of interest, we calculate for these control variables the first two years average for each period.

We match the three data sets together using the French firms national identification number contained by every data set. Most of the trading firms in the fiscal data set (see below) are found in the international trade data set. Our estimation sample is the intersection of the three data sets described above. This represents around 9,000 companies observed for 5 periods: 1998-2000, 2002-2004, 2004-2006, 2006-2008, and 2008-2010. As most companies surveyed by the CIS are also present in the trade data set, the limiting factor is the presence in the CIS data set. It is important to note that our final sample is unbalanced as several firms are only observed for one period. Few observations are dropped because one of the two years needed to calculate the average for the control variables is missing. Overall, we cover around 30 2-digits NACE industries. Table 6 in Appendix 7 presents a full list of variables used in this analysis and their definitions. Table 7 in Appendix 7 provides summary statistics of the main variables.

4.4 Other data

Real exchange rates, used to compute the instrumental variable, are calculated from annual average nominal exchange rates. Data on nominal exchange rates come from

web-site of the French National Institute of Statistics and Economic Studies at http://www.insee.fr/en/methodes/default.asp?page=definitions/enquete-annuelle-entreprises.htm.

[27]FARE stands for Approached File of ESANE Results. ESANE stands for Annual Business Statistics Production. No web page in English exists at the time we write this paper.

International Monetary Fund (2015). We convert NER_{ct} from National currency per USD to National currency per EUR as the French trade data are expressed in Euros. To do that we use data on the exchange rate for the French currency expressed in EUR per USD from Organisation for Economic Development and Cooperation (2014).

To obtain real exchange rates, we use the following formula:

$$RER_{ct} = NER_{ct} \frac{PI_{ct}}{PI_{France,t}} \tag{4.1}$$

where RER_{ct} is Real Exchange Rate from country's c currency to Euro, NER_{ct} is Nominal Exchange Rate from country's c currency to Euro, PI_{ct} is the price index of country c, and $PI_{France,t}$ is the price index of France. Ideally, we would use the production price index of the industrial sector for PI_{ct} and the consumer price index of industrial product for $PI_{France,t}$. Unfortunately, these data are not available for the majority of the countries that export to France. We do not use the GDP deflator as a price index because it also captures economic activities that are not included in the industry. Instead, we compute an export price index of country c for PI_{ct} and an import price index for France. The ideas is that we restrict the price index to commodities that are produced in the different countries and consumed in France.

To compute export price indices and import price indices, we follow Gaulier, Martin, Méjean, and Zignago (2008) methodology. We use trade data from BACI in which trade values do not include freight and insurances. We use unit value to proxy prices. We drop price variations that seem "unrealistic". We define as unrealistic any price evolution (ratio between the current price and the price of the base year) for an exporter c, an importer d, and a good g, that is higher or lower by a factor 3 than the median price evolution for a good g across all countries. We choose 1995 as the base year.

We compute fixed-base price indices because they are more robust to outliers than chained indices. This choice excludes extensive variation in the good basket of the country pair cd that is new goods or disappearing goods are not included in the good basket. This should not be a problem given that 6-digit codes aggregates several goods. We use the Tornqvist formula as it the exact price index for the translog function so that we do not make any assumption on the elasticities of substitution. The resulting distributions of price indices in figure 1 of the appendix does not seem unrealistic.

Another way to check whether the computed price indices are realistic is to compute correlations between the export price index, the GDP deflator and the consumer price index. Table 15 of the appendix shows the correlations between the different price indices. The correlations between the EPI and the GDP deflator is higher than the correlation of the GDP deflator with the other price indices. The IPI is more correlated with the CPI than the EPI. These resultsare consistent with our expectations.

Country real GDP per capita, used to define low production cost countries, are based on purchasing power parity and are expressed in constant 2011 international dollars. Data come from the International Comparison Program database of the World Bank.

5 Importing from low production cost countries and innovation

This Section presents the outcomes of our main estimations. As our econometric model is non-linear we then interpret our findings and discuss the magnitudes of the effects.

5.1 Main results

Table 2 presents our main results. We investigate the impact of firms' share of imports from low production cost countries on the importance given to two kinds of innovations (see equation 3.1).[28] In column 1, 2, and 3, the dependent variable is a dummy equals to 1 when material saving innovations are of moderate or high importance and zero otherwise. In column 4, 5, and 6, the dependent variable is a dummy equals to 1 when product innovations are of moderate or high importance and zero otherwise. Column 1 and column 4 report our baseline TSLS-Probit estimations. Column 2 and 5 report the estimations using a simple Probit estimator where all the regressors are lagged. Finally, column 3 and 6 report simple Probit estimations of equation (3.1). The simple Probit estimations allow us checking the robustness of our instrumental variable strategy.[29]

We find that the share of 'material' products imported from low production cost countries has a negative and significant effect on firms propensity to introduce material or energy saving innovations. We also find that the share of products imported from low production countries has a positive and significant impact on firms propensity to develop new products. The baseline coefficient is -0.447 for material saving innovations and 0.987 for product innovations. Therefore, the effect of offshoring is stronger for product innovations than for material saving innovations. The F-statistics of the first stage regressions are both higher than 25 and suggests that the instrumental variable is

[28]See Section 4 or table 6 in Appendix 7 for a detailed description of the variables.

[29]Using lagged regressors usually requires a weaker identifying assumption but can reduce drastically the sample size.

strong. As expected, the real exchange rate index computed using equation (3.2) has a significant positive impact on the share of imports from low production cost countries.[30]

Our results suggest two things. First, if a firm has been relying relatively more on imports of materials from developing economies, it has fewer incentives to engage in innovative activity that brings environmental benefits. It is likely that cheaper inputs make the prospect of paying out a fixed cost to engage in input-reducing innovation less attractive as the marginal benefits of reducing material or energy use would be smaller for import-reliant firms. Therefore, there is a direct trade-off between importing cheaper inputs and trying to reduce their use by way of introducing a new technology. Second, if a firm has been offshoring to low production cost countries, it has more incentives to develop new products. As the price of input decreases due to offshoring, production costs decrease which increases the firm's potential market share. This market size effect increases the returns for a firm from introducing a product of higher quality or a fully new variety and therefore encourages this type of innovation.

These findings are robust across the various models. Column 2 and 3 report significant and negative coefficients while column 5 and 6 report significant and positive coefficients. Both simple Probit estimation in column 3 and 6 report a coefficient that is lower in absolute value than the baseline TSLS-Probit estimation. This suggests that our identification strategy is successful at declining the attenuation bias due to measurement errors in the main independent variable. As a further check, we estimate model (3.1) without the control variables except the period, industry, and region dummies. Removing the controls does not affect the results as we find coefficients of similar size.[31] In summary, our results offer strong empirical support for our two theoretical predictions.[32]

5.2 Magnitudes

The non-linear nature of probit models does not allow us to interpret the coefficients in table 2 straight away. In order to assign some economic significance to these magnitudes, we calculate the change in the predicted outcome probability in two scenarios - an increase in the import share of products from low production cost countries by 1 standard deviation from the sample mean and a more prominent increase of this import share from 25% to 50%. Results are reported in table 3.

The mean values of the imports share for material goods and for all goods are not very high in our data (around 5%). This is due to the large number of zeros in the data set.

[30] First stage regressions estimations results are reported in table 8 of the appendix.

[31] Results available upon request.

[32] Further robustness checks are performed in section 6.

Table 2: Share of imports from low production cost countries and propensity to carry out innovation

	Dependent variable equals 1 if the innovations are of moderate or high importance					
	Material saving innovation			Product innovation		
	TSLS-Probit (1)	Probit with lag (2)	Probit (3)	TSLS-Probit (4)	Probit with lag (5)	Probit (6)
Share of imports from low production cost countries in all imports	-0.447**	-0.761***	-0.240**	0.987***	0.182	0.369**
	(0.186)	(0.227)	(0.100)	(0.272)	(0.350)	(0.148)
Belongs to a group (0/1)	0.052	0.124	0.055	0.017	0.197	0.010
	(0.038)	(0.098)	(0.039)	(0.046)	(0.120)	(0.047)
ln(Size)	0.130**	0.184*	0.130**	-0.000	-0.165	0.010
	(0.055)	(0.109)	(0.058)	(0.069)	(0.154)	(0.071)
Normalized HHI	0.060	-1.460*	0.048	-0.741	-1.681	-0.717
	(0.386)	(0.845)	(0.392)	(0.461)	(1.115)	(0.490)
ln(Average wage)	0.091*	0.060	0.093*	0.119*	0.256*	0.107
	(0.052)	(0.102)	(0.055)	(0.066)	(0.146)	(0.068)
First-stage F statistic	25.01			28.52		
Lagged regressors	No	Yes	No	No	Yes	No
Period dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies (NACE 3 digits)	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	8,798	2,849	8,798	8,798	2,677	8,798
Number of firms	5,204	1,511	5,204	5,204	1,420	5,204

Notes. Standard errors robust to heteroskedasticity and autocorrelation in parentheses $***p < 0.01, **p < 0.05, *p < 0.1$.
All columns include a constant (not reported). HHI is the Herfindahl-Hirschman Index computed at the NACE 3 digits level.
Low production countries are countries with a real GDP per capita lower than 25% of France's real GDP per capita.
For columns 1, 2, and 3, the set of good is restricted to materials. There is no restriction for column 4, 5, and 6.

Table 3: Economic magnitude of the estimated effect

	TSLS-Probit	
	Material or energy saving innovation	Product innovation
1 standard deviation increase in imports from low production cost countries increases propensity to innovate by	**-6.7pp**	**+14.8pp**
25% to 50% increase in imports from low production cost countries increases propensity to innovate by	**-11.1pp**	**+24.7pp**

Notes. Derived after TSLS-Probit estimations in tables above.
Response given in percentage point changes (pp).

There is, however, a substantial heterogeneity amongst firms in their importing behaviour and the standard deviation is therefore quite high. A one standard deviation increase entails a change in the share of imports supplied from low production cost countries from 5% to 20%. Such an increase is predicted to decrease the probability that firms consider material saving innovations as important by 7 percentage points and increases the probability that firms consider increasing the range of their products as important by 15 percentage points. To put this figure into perspective, consider that the share of US imports of intermediate goods coming from China and India has gone from 2.0% in 1990 to 9.5% in 2010. This suggests that, all else being equal, trade with China and India might have significantly reduced environmental innovation and considerably increased product innovation during the past two decades.

An increase in imports share from 25% to 50% illustrates the non-linearity of the impact. The estimated decrease in the probability to engage in green innovation is around 11 percentage points while the estimated increase in the probability to develop new products is around 25 percentage points. The marginal impact of a higher reliance on Southern imports decreases as this reliance grows.

6 Robustness Checks

We have performed a number of robustness checks to corroborate the main results reported in Section 5 and we describe them in this section.

6.1 Instrumental variable

In section 3, we explained that a standard Probit estimate suffers from two sources of bias. The first bias results from the measurement errors in the main independent variable.

These measurement errors cause the naive estimator to be biased towards zero. The second source of bias comes from omitted variables such as the firm's financial capabilities and ownership status. For each omitted variable, its correlation with the dependent variable has the same sign as the correlation with the main independent variable.[33] This generates an upward bias in the naive estimate.

To check the robustness of our instrumental variable strategy, we estimate model (3.1) using an alternative instrumental variable. More specifically, we use the same equation (3.2) but we change the firm × country specific weights. In our baseline instrument, change in real exchange rate are weighted by the sourcing country importance in the firms total imports of goods. We denote these weights "relative weights" as they take into account the contribution of each supplier relative to the others. However, this can be restrictive. A large variation in the real exchange rates from country c's currency to the Euro can make imports from this country significantly attractive for French firms even if this country represented a small share of the total imports.[34] The relative weight may fail to capture such mechanism. Therefore, we propose "absolute weights" as an alternative to "relative weights". Absolute weight are computed as follows:

$$\tilde{w}^{\mathcal{G}}_{ic,p-1} = \frac{\sum_{g \in \mathcal{G}, t \in p-1} M_{icgt}}{\sum_{g, t \in p-1} M_{icgt}} \tag{6.1}$$

When $\mathcal{G} = \mathcal{M}$, the absolute weight of a country equals the share of materials supplied by this country to the firm in total products supplied by this country to the firm. When $\mathcal{G} = \mathcal{P}$, the absolute weight equals 1. Here, the weight of a supplier does not depends on the other suppliers.[35]

Table 9 of the appendix reports the results of the estimations using both types of weight. Column 1 and 3 are the baseline estimates using relative weight presented in section 5.1. Column 2 and 4 show the TSLS-Probit estimation results with the absolute weight described above. Both columns report coefficient significantly different from zero. Column 2 report a coefficient equal to -0.672 which is of similar size than the baseline estimate. However, column 4 reports a coefficient that is 2.5 times larger than our baseline estimate. For the absolute weight first stage estimation, we find F-statistics around 11 which is just above the rule-of-thumb threshold of 10 usually employed by applied econometricians. Using absolute weights yield much weaker instruments than using relative weights. The large coefficient of column 4 and equal to 2.523 is probably

[33]The correlations are both positive for firm's financial capabilities and foreign ownership status.

[34]This methodological issue shares similarities with the measure of tariff.

[35]The methodology for absolute weight are more similar to simple average tariff methodology than relative weight's. It is not possible to take simple average change in real exchange rate between countries as all firms would have the same instrumental variable.

due to the bias provoked by using a weaker instrument. To summarize, our methodology to make our instrument firm specific is not highly sensitive to modifications.

6.2 Low production cost countries definition

Our main estimations use the share of material imports from low wage countries as a proxy for the average cost of inputs. However, this definition of low wage countries based on GDP per capita may not be the most appropriate. Unfortunately, data on wages are not as widely available as data on GDP per capita. To check the sensitivity of our baseline definition of low production cost countries, we run the estimation using alternative definitions of low production cost. More specifically, we define two groups of low production cost countries: the first includes China and India and the second includes non-OECD countries.

Regressions results with the different definitions of low production cost countries are presented in table 10 of the appendix. Column 1 and 5 show the baseline estimates presented in section 5.1 that use 25% France GDP per capita threshold. The share of imports from these two country groups gives results that are very similar to our main outcomes suggesting China and India are the main drivers behind these results. The regression with non-OECD countries yield coefficient that are much less significant. This may be due to the fact that non-OECD countries include countries such as Singapore, South Africa, Russia, and Turkey where the wage is much higher than the wage in India or in China.[36]

Eventually, we perform two placebo or falsification tests. We check whether the main outcomes can be observed for imports from EU members states that are high production cost suppliers. We find that the share of imports from the EU in total imports have a significant positive effect on the introduction of material saving innovation and a significant negative effect on the development of new products. As expected, these effects are the opposite of our baseline results. Overall, these checks highlights that the origin of imports matter for firm-level innovation.

6.3 Imported goods definition

As suggest by our theoretical model, we use in our baseline the share of 'material' imports from low production cost countries when estimating the material saving equation and the share of 'all' imports from low production cost countries when estimating the product innovation equation. To check whether our results are specific to their correct definition of goods, we run estimation where the set of goods are switched. Table11 of

[36]Based on the Labour Statistics Database of the International Labour Organisation.

the appendix show the results of these placebo tests. Column 1 and 4 corresponds to the baseline estimations. Column 2 shows a negative coefficient but that is not statistically different from zero. This shows that our main results on material saving innovation are specific to material goods imported. Column 3 shows a positive coefficient that is lower than our baseline estimate. Consistent with our theory, product innovation react to imports in all goods.

6.4 Other checks

6.4.1 Unobserved heterogeneity

Controlling for unobserved heterogeneity is difficult in discrete panel data models like the one we employ. This is because one cannot difference out the unobserved term using first difference or the within transformation since these models are not linear. Point identification can be achieved for binary panel data model but requires strong assumptions and is not robust to misspecification. For instance, Chamberlain (2010), Honoré (2002), and Honoré and Kyriazidou (2000) show that point identification in parametric discrete panel data model fails unless the time dependent unobservables are independently and identically distributed with a logistic distribution. Manski (1987) shows that point identification is achieved if at least one regressor have unbounded support. Because these identifying assumptions are so strong, recent econometric research focus on partial identification that requires much weaker assumptions. [37] Here, we try to control for as much observed heterogeneity as we can using many firm-level control variables. We also run regressions where we drop different subset of control variables. Estimated coefficient are similar to our main estimates.[38]

6.4.2 Ordered Probit model

In our baseline estimation, we employ a TSLS-Probit estimator. The advantage of TSLS-Probit is that its marginal effect has clearer interpretation than the TSLS-Ordered-Probit model. Here, we check whether our methodological choice impact our main results. In table 12 of the appendix, we report the estimations of our structural equation using TSLS-Ordered-Probit instead of TSLS-Probit. We find a significant and negative coefficient for the material saving equation and a significant and positive coefficient for the product innovation equation. Therefore, our main results are robust to the choice of the models.[39]

[37] See for instance Chesher (2010), Chesher and Smolinski (2012), Chesher (2013), Chesher and Rosen (2013), and Chesher, Smolinski, and Rosen (2013).

[38] Results available upon request.

[39] Note that the size of the coefficient of TSLS-Ordered-Probit and TSLS-Probit are not directly comparable.

6.4.3 Sample selection issue

Sample selection may be another empirical issue we have to address. In our data, only firms that innovate at period p actually provide a score for environmental innovation. Therefore, innovative firms are selected. The solution we adopt is standard and consists in two steps. In the first step, we estimate a Probit selection model where the dependent variable is a binary variable equals to 1 when the firm innovates:

$$Pr\left(Innov_{ip}=1\right)=\Phi\left(\alpha ImportShare_{ip}+\beta X_{ip}+\delta_j+\lambda_p+\eta_r+\gamma Neighbour_{ip}+\upsilon_{it}\right) \tag{6.2}$$

where Φ is the cumulative normal distribution. $Neighbour_{ip}$ is the selection variable that influences the probability that firms i innovate in general but shall not impact the importance of material saving innovation or product innovation. The selection variable is calculated as the ratio between the number of firms in the same 3-digits NACE industry as i that are located in the same geographical area and that introduce at least one innovation in period p and the total number of firms in that same industry and in that same geographical area.[40] If other firms competing in the same market are innovative, it provides more incentives for any firms to innovate as well. In addition, innovations made by some firms may also spill over to some other firms. Thus, we expect γ to be positive. Conditional on the other regressors, we do not believe that $Neighbour_{ip}$ impacts the score of environmental innovation in equation 3.1 so that it is a valid exclusion restriction.

The second step of our identification strategy is to include the inverse Mills ratio as an additional control in our final structural equation:

$$Pr\left(Innov^{\mathcal{O}}_{ip}=1\right)=\Phi\left(\alpha ImportShare_{ip}+\beta X_{ip}+\delta_j+\lambda_p+\eta_r+\rho m_{it}+\epsilon_{ip}\right) \tag{6.3}$$

where m_{it} is the inverse Mills ratio obtained from the Probit selection model 6.2 and calculated for each period. We expect ρ to be positive and significantly different from 0.

Table 13 of the appendix report the estimations when we correct or not for sample selection.[41] We find that controlling for sample selection does not impact the results. The coefficients found are highly similar and the inverse mills ratio is not statistically different from zero.

[40] Here, the geographical area is the French department. The departments are administrative divisions of France and amount to a number of 101.

[41] The estimation sample is smaller than in the baseline since the selection variable $Neighbour_{ip}$ is not as widely available as the other controls.

6.4.4 Outlying observations

To make sure some outlying influential observations do not affect the pattern of our findings we removed the top and bottom 5% of firms in terms of main control variables. Table 14 of the appendix show the results. Our findings remain unchanged but the coefficients are of higher magnitudes to those reported as the main results. As firms are not randomly dropped from the baseline sample, the estimated coefficient are biased. Nevertheless, our findings about the direction of the innovation are robust.

6.4.5 Over-reporting

There may be a concern pertaining to companies wishing to look more environmentally-friendly and thus over-reporting 'green' innovations. Since we find that the 'material' imports reduce the propensity to introduce an environmental innovation, if companies indeed over-report these innovations, then our findings would represent a lower bound of estimates.

7 Conclusion

In this paper, we combine firm-level trade and financial data with information on innovation activities to examine the impact of trade with low production cost countries on clean innovation and product innovation. Our data covers close to 9,000 French companies observed from 1998 to 2010. Consistent with our theoretical prediction, we find robust evidence that firms importing a higher share of their inputs from Southern countries are less likely to engage in 'clean' innovation that reduces material or energy use per unit of output and more likely to develop new products or services. In other words, trade affects the direction of technological change. This finding is stable across various definitions of the group of countries used to define imports from Southern countries and formula used in the instrumental variable computation. Consistent with our theoretical model, our results on material saving innovation are specific to import in materials. Our main results focus on China and India, but our findings are robust to considering all low-wage countries. The magnitude of the effect is large: at the sample mean, an increase in the import share of products from low wage countries in a firm's total imports by one standard deviation (a move from 5% to 20%) is predicted to decrease the firm's propensity to engage in environmental innovation by 7 percentage points and predicted to increase the firm's propensity to develop new products by 15 percentage points. Since the share of US imports of intermediate goods coming from China and India has gone from 2.0% in 1990 to 9.5% in 2010, this finding suggests that trade with low-cost countries have significantly reduced environmental innovation in developed countries during the past two decades.

This paper has important policy implications. Our findings suggest that carbon leakage may not only affect jobs and emissions in the short run. It also affects long-run competitiveness by reducing incentives for firms to conduct innovation in 'clean' technologies. This may provide further justification for policies aimed at preventing 'leakage' such as border-tax adjustment.

Our work could be extended in several directions. However, an obvious limitation is that we do not fully control for time invariant unobserved heterogeneity since we rely on discrete choice models.

References

Acemoglu, D., P. Aghion, L. Bursztyn, and D. Hemous (2012): “The Environment and Directed Technical Change,” *American Economic Review*, 102(1), 131–166.

Aghion, P., S. Bechtold, L. Cassar, and H. Herz (2014): “The causal effects of competition on innovation: Experimental Evidence,” Discussion paper, National Bureau of Economic Research.

Aghion, P., N. Bloom, R. Blundell, R. Griffith, and P. Howitt (2005): “Competition and Innovation: an Inverted-U Relationship,” *The Quarterly Journal of Economics*, 120(2), 701–728.

Aghion, P., A. Dechezleprêtre, D. Hemous, R. Martin, and J. V. Reenen (2012): “Carbon Taxes, Path Dependency and Directed Technical Change: Evidence from the Auto Industry,” NBER Working Paper No. 18596. Cambridge, MA: National Bureau of Economic Research.

Aldy, J. E., and W. A. Pizer (2011): “The Competitiveness Impacts of Climate Change Mitigation Policies,” NBER Working Paper No. 17705. Cambridge, MA: National Bureau of Economic Research.

Andersson, M., H. Lööf, and S. Johansson (2008): “Productivity and International Trade: Firm Level Evidence from a Small Open Economy,” *Review of World Economics (Weltwirtschaftliches Archiv)*, 144(4), 774–801.

Bernard, A. B., J. B. Jensen, and P. K. Schott (2006): “Survival of the best fit: Exposure to low-wage countries and the (uneven) growth of U.S. manufacturing plants,” *Journal of International Economics*, 68(1), 219–237.

Bloom, N., M. Draca, and J. V. Reenen (2011): “Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity,” NBER Working Paper No. 16717. Cambridge, MA: National Bureau of Economic Research.

Blundell, R., R. Griffith, and J. Van Reenen (1995): “Dynamic count data models of technological innovation,” *The Economic Journal*, pp. 333–344.

Bøler, E. A., A. Moxnes, and K.-H. Ulltveit-Moe (2015): “R&D, International Sourcing, and the Joint Impact on Firm Performance,” American Economic Review.

Brunnermeier, S. B., and M. A. Cohen (2003): “Determinants of environmental innovation in US manufacturing industries,” *Journal of Environmental Economics and Management*, 45(2), 278–293.

Castellani, D., F. Serti, and C. Tomasi (2010): "Firms in International Trade: Importers' and Exporters' Heterogeneity in Italian Manufacturing Industry," *The World Economy*, 33(3), 424–457.

Chamberlain, G. (2010): "Binary Response Models for Panel Data: Identification and Information," *Econometrica*, 78(1), 159–168.

Chesher, A. (2010): "Instrumental variable models for discrete outcomes," *Econometrica*, 78(2), 575–601.

——— (2013): "Semiparametric structural models of binary response: shape restrictions and partial identification," *Econometric Theory*, 29(02), 231–266.

Chesher, A., and A. M. Rosen (2013): "What do instrumental variable models deliver with discrete dependent variables?," *American Economic Review*, 103(3), 557–562.

Chesher, A., and K. Smolinski (2012): "IV models of ordered choice," *Journal of Econometrics*, 166(1), 33–48.

Chesher, A., K. Smolinski, and A. M. Rosen (2013): "An instrumental variable model of multiple discrete choice," *Quantitative Economics*, 4(2), 157–196.

Colantone, I., and R. Crinó (2011): "New Imported Inputs, New Domestic Products," Development Working Papers 312. Centro Studi Luca DÁgliano, University of Milano.

Dachs, B., B. Ebersberger, S. Kinkel, and O. Som (2014): "The effects of production offshoring on R&D and innovation in the home country," *Economia e Politica Industriale*, 42(1), 9–31.

Ederington, J., A. Levinson, and J. Minier (2005): "Footloose and Pollution-Free," *The Review of Economics and Statistics*, 87(1), 92–99.

Frondel, M., J. Horbach, and K. Rennings (2008): "What triggers environmental management and innovation? Empirical evidence for Germany," *Ecological Economics*, 66(1), 153–160.

Gaulier, G., J. Martin, I. Méjean, and S. Zignago (2008): "International trade price indices," .

Geroski, P. (1995): "Market Structure, Corporate Performance and Innovative Activity," Discussion paper, Oxford: Oxford University Press.

Ghisetti, C., and F. Pontoni (2015): "Investigating policy and R&D effects on environmental innovation: A meta-analysis," *Ecological Economics*, 118, 57 – 66.

Goldberg, P. K., A. K. Khandelwal, N. Pavcnik, and P. Topalova (2010): "Imported Intermediate Inputs and Domestic Product Growth: Evidence from India," *The Quarterly Journal of Economics*, 125(4), 1727–1767.

Grossman, G. M., and E. Helpman (1991): "Quality Ladders and Product Cycles," *The Quarterly Journal of Economics*, 106(2), 557–86.

Halpern, L., M. s. Koren, and A. Szeidl (2015): "Imported Inputs and Productivity," *American Economic Review*, 105(12), 3660–3703.

Honoré, B. E. (2002): "Nonlinear models with panel data," *Portuguese Economic Journal*, 1(2), 163–179.

Honoré, B. E., and E. Kyriazidou (2000): "Panel data discrete choice models with lagged dependent variables," *Econometrica*, pp. 839–874.

Horbach, J. (2008): "Determinants of environmental innovation–New evidence from German panel data sources," *Research Policy*, 37(1), 163–173.

Horbach, J., and K. Rennings (2012): "Environmental innovation and employment dynamics in different technology fields: An analysis based on the German community innovation survey 2009," ZEW Discussion Paper No. 12-006. Zentrum für Europäische Wirtschaftsforschung (Center for European Economic Research).

Iacovone, L., F. Rauch, and L. A. Winters (2010): "Trade as an Engine of Creative Destruction: Mexican Experience with Chinese Competition," CEP Discussion Paper No. 999.

International Monetary Fund (2015): "International Financial Statistics (Edition: August 2015)," UK Data Service.

Johnstone, N., I. Haščič, and D. Popp (2010): "Renewable Energy Policies and Technological Innovation: Evidence Based on Patent Counts," *Environmental & Resource Economics*, 45(1), 133–155.

Kasahara, H., and B. Lapham (2008): "Productivity and the Decision to Import and Export: Theory and Evidence," CESifo Working Paper No. 2240.

Kellenberg, D. K. (2009): "An empirical investigation of the pollution haven effect with strategic environment and trade policy," *Journal of international economics*, 78(2), 242–255.

Kheder, S. B., and N. Zugravu (2012): "Environmental regulation and French firms location abroad: An economic geography model in an international comparative study," *Ecological Economics*, 77, 48–61.

Leeuwen, G. v., and P. Mohnen (2013): "Revisiting the porter hypothesis: An empirical analysis of green innovation for the Netherlands," *CIRANO-Scientific Publications Research Paper*, (2013s-02).

Lelarge, C., and B. Nefussi (2013): "The Dynamics of Firms's Product Portfolios in Response to International Competition: Evidence from French Firms," .

Levinson, A., and M. S. Taylor (2008): "Unmasking the Pollution Haven Effect," *International Economic Review*, 49(1), 223–254.

Manski, C. F. (1987): "Semiparametric analysis of random effects linear models from binary panel data," *Econometrica: Journal of the Econometric Society*, pp. 357–362.

Newell, R. G., A. B. Jaffe, and R. N. Stavins (1999): "The Induced Innovation Hypothesis And Energy-Saving Technological Change," *The Quarterly Journal of Economics*, 114(3), 941–975.

Nickell, S. J. (1996): "Competition and corporate performance," *Journal of political economy*, pp. 724–746.

Organisation for Economic Development and Cooperation (2014): "Monthly Statistics of International Trade (Data downloaded 4th Feb 2015)," UK Data Service.

Popp, D. (2002): "Induced Innovation and Energy Prices," *American Economic Review*, 92(1), 160–180.

Rennings, K., and C. Rammer (2011): "The Impact of Regulation-Driven Environmental Innovation on Innovation Success and Firm Performance," *Industry and Innovation*, 18(3), 255–283.

Rennings, K., and S. Rexhäuser (2010): "Long-term impacts of environmental policy and eco-innovative activities of firms," ZEW Discussion Paper No. 10-074. Zentrum für Europäische Wirtschaftsforschung (Center for European Economic Research).

Rexhäuser, S., and C. Rammer (2011): "Unmasking the Porter hypothesis: Environmental innovations and firm-profitability," ZEW Discussion Paper No. 11-036. Zentrum für Europäische Wirtschaftsforschung (Center for European Economic Research).

Veugelers, R. (2012): "Which policy instruments to induce clean innovating?," *Research Policy*, 41(10), 1770–1778.

Vogel, A., and J. Wagner (2010): "Higher productivity in importing German manufacturing firms: self-selection, learning from importing, or both?," *Review of World Economics (Weltwirtschaftliches Archiv)*, 145(4), 641–665.

Appendix

Table 4: Harmonized System 2 digits codes for 'material' goods

Material subcategory	**HS code**	**Description**
minerals and mining	25	Salt, sulphur, earth, stone, plaster, lime and cement
minerals and mining	26	Ores, slag and ash
chemicals	28	Inorganic chemicals, precious metal compound, isotopes
chemicals	29	Organic chemicals
plastics	39	Plastics and articles thereof
forest products	44	Wood and articles of wood, wood charcoal
paper	47	Pulp of wood, fibrous cellulosic material, waste etc
paper include packaging products	48	Paper & paperboard, articles of pulp, paper and board
construction materials	68	Stone, plaster, cement, asbestos, mica, etc articles
glass	70	Glass and glassware
metals	72	Iron and steel
metals	73	Articles of iron or steel
metals	74	Copper and articles thereof
metals	75	Nickel and articles thereof
metals	76	Aluminium and articles thereof
metals	78	Lead and articles thereof
metals	79	Zinc and articles thereof
metals	80	Tin and articles thereof
metals	81	Other base metals, cermets, articles thereof

Table 5: Countries with real GDP per capita lower than 25% of France's

Afghanistan	Djibouti	Laos	Samoa
Albania	Dominica	Lesotho	Sao Tome and Principe
Angola	Dominican Republic	Liberia	Senegal
Armenia	Ecuador	Madagascar	Sierra Leone
Azerbaijan	Egypt	Malawi	Solomon Islands
Bangladesh	El Salvador	Mali	Sri Lanka
Belize	Eritrea	Marshall Islands	State of Palestine
Benin	Ethiopia	Mauritania	Sudan
Bhutan	Fiji	Micronesia	Swaziland
Bolivia	Gambia	Moldova	Tajikistan
Bosnia and Herzegovina	Georgia	Mongolia	Tanzania
Burkina Faso	Ghana	Morocco	Timor-Leste
Burundi	Guatemala	Mozambique	Togo
Cambodia	Guinea	Namibia	Tonga
Cameroon	Guinea-Bissau	Nepal	Tunisia
Cape Verde	Guyana	Nicaragua	Turkmenistan
Central African Republic	Haiti	Niger	Tuvalu
Chad	Honduras	Nigeria	Uganda
China	India	Pakistan	Ukraine
Colombia	Indonesia	Papua New Guinea	Uzbekistan
Comoros	Jordan	Paraguay	Vanuatu
Congo	Kenya	Peru	Viet Nam
Cte d'Ivoire	Kiribati	Philippines	Yemen
Democratic Republic of the Congo	Kyrgyzstan	Rwanda	Zambia
			Zimbabwe

Notes. List of countries based on 2004 real GDP per capita. In the data, yearly changes in GDP per capita are taken into account.

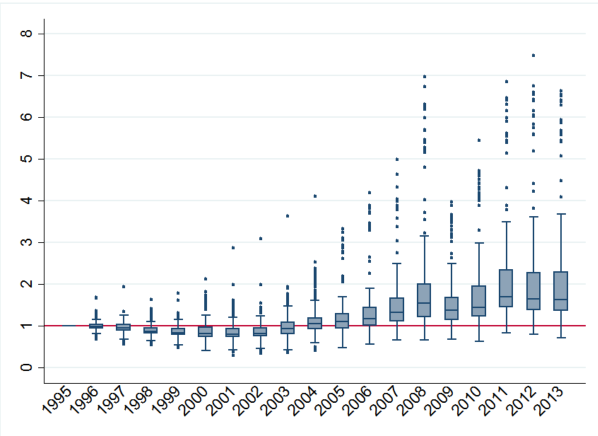
Table 6: Definition of variables

Variable	Description
Material saving innovation	Reported score for the question "How important were innovations that reduce either use of energy or material per unit of output in your decision to innovate?" 0 - Not relevant, 1 - Low, 2 - Moderate, 3 - High.
Material saving innovation (0/1)	1 if a firm answered moderate, or high to the question above.
Product innovation	Reported score for the question "How important were innovations that increase the range of products (goods and service) in your decision to innovate?" 0 - Not relevant, 1 - Low, 2 - Moderate, 3 - High.
Product innovation (0/1)	1 if a firm answered moderate, or high to the question above.
Share of 'material' imports from low production cost countries	Value of 'material' products from countries which real GDP per capita is lower than 25% of France's real GDP per capita in total value of firm's 'material' imports per year.
Share of imports from low production cost countries	Value of products from countries which real GDP per capita is lower than 25% of France's real GDP per capita in total value of firm's imports per year.
Belongs to a group (0/1)	Dummy variable equal to 1 if a firm belongs to a group and 0 otherwise.
Size	Total number of employees.
Normalized HHI	Normalized Herfindahl-Hirschman Index computed at the NACE 3 digits level.
Average wage	Total wages paid divided by the number of employees in thousand euros.

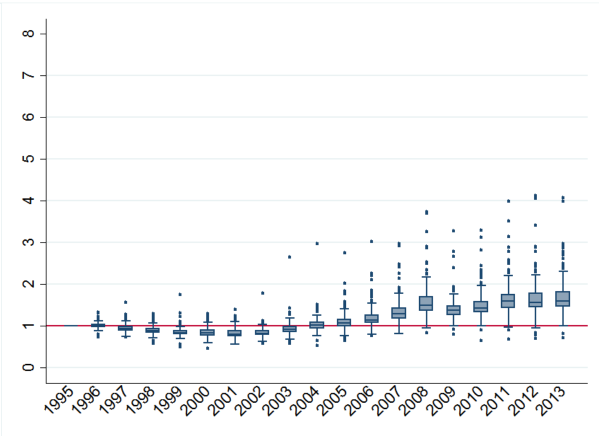
Notes. Material products are intermediate goods that are not 'complex' e.g. primary plastic, crude steel, wood pulp, etcetera. Energy intensive goods consist in fuels and products from industries covered by the EU-ETS e.g. coal, crude steel, fertilizers, etcetera.

Table 7: Summary statistics

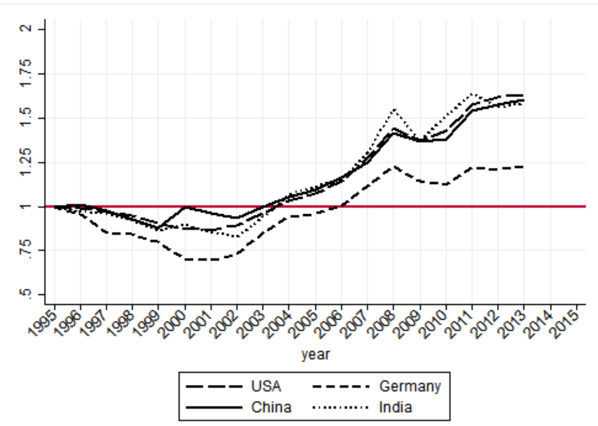
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Material saving innovation (0/1)	8,798	0.488	0.500	0	1
Product innovation (0/1)	8,798	0.862	0.345	0	1
Share of 'material' imports from low production cost countries in all 'material' imports	8,798	0.045	0.153	0	1
Share of imports from low production cost countries in all imports	8,798	0.054	0.143	0	1
Belongs to a group (0/1)	8,798	0.768	0.422	0	1
ln($Size$)	8,798	5.198	1.369	0	11.199
Normalized HHI	8,798	0.043	0.064	0.001	0.654
ln(Average wage)	8,798	8.573	1.451	4.538	14.985



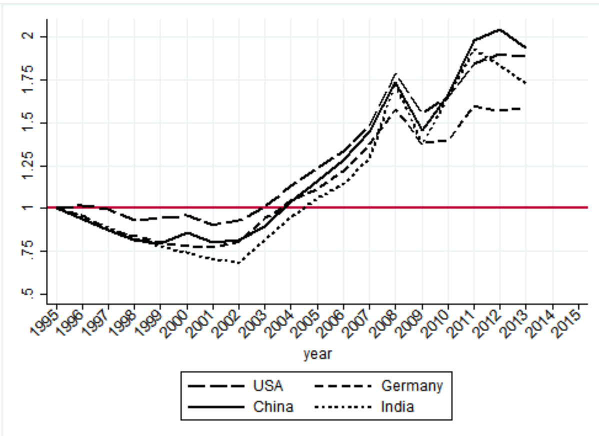
(a) Export Price Index Distribution



(b) Import Price Index Distribution



(c) Export Price Index for selected countries



(d) Import Price Index for selected countries

Figure 1: Commodity Price Indices using BACI trade data

Table 8: First stage regressions

	Dependent variable equals share of imports from low production cost countries in all imports	
	OLS	
	Material saving innovation (1)	Product innovation (2)
Real Exchange Rate Index	0.535***	0.478***
	(0.010)	(0.009)
Belongs to a group (0/1)	-0.011***	-0.011***
	(0.004)	(0.003)
ln(Size)	0.002	0.014***
	(0.005)	(0.005)
Normalized HHI	0.077**	0.017
	(0.038)	(0.035)
ln(Average wage)	-0.005	-0.017***
	(0.005)	(0.005)
First-stage F statistic	25.01	28.52
Lagged regressors	No	No
Period dummies	Yes	Yes
Industry dummies (NACE 3 digits)	Yes	Yes
Region dummies	Yes	Yes
Number of observations	8,798	8,798
Number of firms	5,204	5,204

Notes. Standard errors robust to heteroskedasticity and autocorrelation in parentheses $***p < 0.01, **p < 0.05, *p < 0.1$. All columns include a constant (not reported). HHI is the Herfindahl-Hirschman Index computed at the NACE 3 digits level. Low production countries are countries with a real GDP per capita lower than 25% of France's real GDP per capita. For columns 1 the set of good is restricted to materials. There is no restriction for column 4.

Table 9: Instrumental variable computation methodology

	Dependent variable equals 1 if the innovations are of moderate or high importance			
	TSLS-Probit			
	Material saving innovation		Product innovation	
	Relative weight (1)	Absolute weight (2)	Relative weight (3)	Absolute weight (4)
Share of imports from low production cost production countries in all imports	-0.447**	-0.672**	0.987***	2.523***
	(0.186)	(0.287)	(0.272)	(0.530)
Belongs to a group (0/1)	0.052	0.049	0.017	0.035
	(0.038)	(0.038)	(0.046)	(0.047)
ln(Size)	0.130**	0.131**	-0.000	-0.024
	(0.055)	(0.055)	(0.069)	(0.071)
Normalized HHI	0.060	0.073	-0.741	-0.835*
	(0.386)	(0.387)	(0.461)	(0.470)
ln(Average wage)	0.091*	0.089*	0.119*	0.149**
	(0.052)	(0.053)	(0.066)	(0.068)
First-stage F statistic	25.01	11.34	28.52	11.52
Lagged regressors	No	No	No	No
Period dummies	Yes	Yes	Yes	Yes
Industry dummies (NACE 3 digits)	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes
Number of observations	8,798	8,798	8,798	8,798
Number of firms	5,204	5,204	5,204	5,204

Notes. Standard errors robust to heteroskedasticity and autocorrelation in parentheses $***p < 0.01, **p < 0.05, *p < 0.1$. All columns include a constant (not reported). HHI is the Herfindahl-Hirschman Index computed at the NACE 3 digits level. The EU member states are used as a placebo test.

Table 10: Various definitions of low production cost countries

	Dependent variable equals 1 if the innovations are of moderate or high importance							
	TSLS-Probit							
	Material saving innovation				Product innovation			
	Low wage 25%	China and India	Non OECD	EU	Low wage 25%	China and India	Non OECD	EU
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of imports from low production cost production countries in all imports	-0.447**	-0.458**	-0.209*	0.164**	0.987***	0.755***	0.232	-0.174*
	(0.186)	(0.197)	(0.117)	(0.075)	(0.272)	(0.275)	(0.146)	(0.099)
Belongs to a group (0/1)	0.052	0.053	0.054	0.056	0.017	0.011	0.009	0.008
	(0.038)	(0.038)	(0.038)	(0.038)	(0.046)	(0.046)	(0.046)	(0.046)
ln(Size)	0.130**	0.127**	0.129**	0.119**	-0.000	0.012	0.015	0.026
	(0.055)	(0.055)	(0.055)	(0.055)	(0.069)	(0.069)	(0.069)	(0.069)
Normalized HHI	0.060	0.065	0.040	0.077	-0.741	-0.717	-0.712	-0.750
	(0.386)	(0.386)	(0.386)	(0.387)	(0.461)	(0.460)	(0.460)	(0.461)
ln(Average wage)	0.091*	0.094*	0.094*	0.104**	0.119*	0.107	0.101	0.090
	(0.052)	(0.052)	(0.052)	(0.053)	(0.066)	(0.066)	(0.066)	(0.066)
First-stage F statistic	25.01	31.92	28.07	34.15	28.52	44.01	39.23	41.44
Lagged regressors	No	No	No	No	No	No	No	No
Period dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies (NACE 3 digits)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	8,971	8,971	8,971	8,971	8,971	8,971	8,971	8,971
Number of firms	5,288	5,288	5,288	5,288	5,288	5,288	5,288	5,288

Notes. Standard errors robust to heteroskedasticity and autocorrelation in parentheses $***p < 0.01, **p < 0.05, *p < 0.1$. All columns include a constant (not reported). HHI is the Herfindahl-Hirschman Index computed at the NACE 3 digits level. The EU member states are used as a placebo test.

Table 11: Effect specific to material goods

	Dependent variable equals 1 if the innovations are of moderate or high importance			
	TSLS-Probit			
	Material saving innovation		Product innovation	
	Material (1)	All (2)	Material (3)	All (4)
Share of imports from low production cost production countries in all imports	-0.447** (0.186)	-0.280 (0.199)	0.579** (0.245)	0.987*** (0.272)
Belongs to a group (0/1)	0.052 (0.038)	0.054 (0.038)	0.013 (0.046)	0.017 (0.046)
ln(Size)	0.130** (0.055)	0.133** (0.055)	0.012 (0.069)	-0.000 (0.069)
Normalized HHI	0.060 (0.386)	0.055 (0.386)	-0.731 (0.460)	-0.741 (0.461)
ln(Average wage)	0.091* (0.052)	0.090* (0.053)	0.106 (0.066)	0.119* (0.066)
First-stage F statistic	25.01	28.52	25.01	28.52
Lagged regressors	No	No	No	No
Period dummies	Yes	Yes	Yes	Yes
Industry dummies (NACE 3 digits)	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes
Number of observations	8,798	8,798	8,798	8,798
Number of firms	5,204	5,204	5,204	5,204

Notes. Standard errors robust to heteroskedasticity and autocorrelation in parentheses $***p < 0.01, **p < 0.05, *p < 0.1$. All columns include a constant (not reported). HHI is the Herfindahl-Hirschman Index computed at the NACE 3 digits level. Low production countries are countries with a real GDP per capita lower than 25% of France real GDP per capita. ETS goods include goods produced by industry under the European Emission Trading Scheme. From the baseline estimation, we lose 700 observations because the ETS good group contains fewer HS6 goods than the material groups. Thus, the denominators of the main independent variable for several firms equal zero.

Table 12: Ordered Probit model

	Dependent variable equals 1 if the innovations are of moderate or high importance	
	TSLS-Ordered-Probit	
	Material saving innovation (1)	Product innovation (2)
Share of imports from low production cost countries in all imports	-0.334**	0.585***
	(0.157)	(0.172)
Belongs to a group (0/1)	0.058*	-0.004
	(0.033)	(0.034)
ln(Size)	0.131***	-0.010
	(0.048)	(0.048)
Normalized HHI	-0.055	-0.248
	(0.337)	(0.378)
ln(Average wage)	0.069	0.111**
	(0.046)	(0.047)
First-stage IV coefficient	0.539***	0.499***
	(0.029)	(0.025)
Lagged regressors	No	No
Period dummies	Yes	Yes
Industry dummies (NACE 3 digits)	Yes	Yes
Region dummies	Yes	Yes
Number of observations	8,971	9,964
Number of firms	5,288	6,080

Notes. Standard errors robust to heteroskedasticity and autocorrelation in parentheses $***p < 0.01, **p < 0.05, *p < 0.1$. All columns include a constant (not reported). HHI is the Herfindahl-Hirschman Index computed at the NACE 3 digits level. Low production countries are countries with a real GDP per capita lower than 25% of France's real GDP per capita. For columns 1, 2, and 3, the set of good is restricted to materials. There is no restriction for column 4, 5, and 6.

Table 13: Correction for sample selection

	Dependent variable equals 1 if the innovations are of moderate or high importance			
	TSLS-Probit			
	Material saving innovation		Product innovation	
	No correction	Correction	No correction	Correction
	(1)	(2)	(3)	(4)
Share of imports from low production cost production countries in all imports	-0.511**	-0.463**	1.154***	1.171***
	(0.207)	(0.213)	(0.323)	(0.342)
Belongs to a group (0/1)	0.075*	0.112**	-0.013	-0.006
	(0.043)	(0.054)	(0.053)	(0.068)
ln(Size)	0.168***	0.203***	0.073	0.080
	(0.059)	(0.067)	(0.076)	(0.086)
Normalized HHI	0.104	0.290	-0.084	-0.047
	(0.487)	(0.515)	(0.648)	(0.611)
ln(Average wage)	0.031	0.041	0.079	0.082
	(0.057)	(0.057)	(0.073)	(0.074)
Inverse Mills Ratio		0.273		0.058
		(0.243)		(0.312)
First-stage F statistic	21.85	21.76	23.56	23.44
Lagged regressors	No	No	No	No
Period dummies	Yes	Yes	Yes	Yes
Industry dummies (NACE 3 digits)	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes
Number of observations	6,941	6,941	6,935	6,935
Number of firms	4,534	4,534	4,530	4,530

Notes. Standard errors robust to heteroskedasticity and autocorrelation in parentheses $***p < 0.01, **p < 0.05, *p < 0.1$. All columns include a constant (not reported). HHI is the Herfindahl-Hirschman Index computed at the NACE 3 digits level. Low production countries are countries with a real GDP per capita lower than 25% of France real GDP per capita. ETS goods include goods produced by industry under the European Emission Trading Scheme. From the baseline estimation, we lose 700 observations because the ETS good group contains fewer HS6 goods than the material groups. Thus, the denominators of the main independent variable for several firms equal zero.

Table 14: Sample restricted to the percentiles below 95%

	Dependent variable equals 1 if the innovations are of moderate or high importance	
	TSLS-Probit	
	Material saving innovation (1)	Product innovation (2)
Share of imports from low production cost production countries in all imports	-2.962**	2.646***
	(1.408)	(0.887)
Belongs to a group (0/1)	0.068*	-0.021
	(0.039)	(0.043)
ln(Size)	0.140**	0.047
	(0.056)	(0.063)
Normalized HHI	0.027	-0.751*
	(0.397)	(0.442)
ln(Average wage)	0.088*	0.068
	(0.053)	(0.060)
First-stage F statistic	7.43	14.28
Lagged regressors	No	No
Period dummies	Yes	Yes
Industry dummies (NACE 3 digits)	Yes	Yes
Region dummies	Yes	Yes
Number of observations	8,502	9,434
Number of firms	5,057	5,781

Notes. Standard errors robust to heteroskedasticity and autocorrelation in parentheses $***p < 0.01, **p < 0.05, *p < 0.1$. All columns include a constant (not reported). HHI is the Herfindahl-Hirschman Index computed at the NACE 3 digits level. Low production countries are countries with a real GDP per capita lower than 25% of France's real GDP per capita. For columns 1 the set of good is restricted to materials. There is no restriction for column 4.

Table 15: Correlations between price indices and number of country×year

	Exporter Price Index	GDP deflator	Importer Price Index	Consumer Price Index
Exporter Price Index	1			
	3,097			
GDP deflator	0.26***	1		
	3,009	4,192		
Importer Price Index	0.42***	0.02	1	
	3,097	3,211	3,363	
Consumer Price Index	0.39***	0.02	0.56***	1
	2,783	3,683	2,982	5,233