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Importing, Outsourcing and Pollution Offshoring

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Abstract

Focusing on Japan over the period 1988-2013, this paper provides the first test of the extent to which pollution offshoring has occurred for this major industrial economy. In so doing, we identify whether the composition of domestic production, imports, overall trade patterns and overseas outsourcing has become more or less pollution intensive. We then focus on the role played by overseas outsourcing in pollution offshoring. Utilising a unique dataset of approximately 4,000 Japanese firms for the period 2009-13, we use propensity score matching and difference-in-differences to examine how a firm's CO_2 emissions intensity is affected by its decision to outsource some of its production overseas. Our results indicate that the composition of Japanese imports appear to have become dirtier and the carbon embodied within Japanese imports is larger and has grown more rapidly than the carbon embodied within exports. We also find that relative to a control group, the growth rate of pollution intensity of firms that begin overseas outsourcing is 7.3 percentage points lower in the year that they start overseas outsourcing and 7.7 percentage points lower in the following year, suggesting that outsourcing is one route through which pollution offshoring is occurring. New importers also experience slower emissions growth but the reduction is less than for new outsourcers.

JEL: F18, F23, L51, L60, Q56, R3
Key words: pollution offshoring, outsourcing, propensity score matching, difference-in-differences.

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1. Introduction

In recent years there has been increasing interest from both academics and policymakers in the relationship between globalisation and the environment and the implications for energy use, and hence pollution, of the growing geographical dislocation between production and consumption.[1] The term pollution offshoring is used to refer to the domestic pollution avoided when firms or consumers use goods produced overseas rather than domestically and several studies have examined the extent to which such offshoring is taking place. If pollution offshoring were occurring then we would expect to see the composition of imports becoming dirtier as they increasingly replace pollution intensive domestic production. However, contrary to expectations Cole (2004) andLevinson (2009, 2010) find that the composition of US imports became cleaner during 1980s and 1990s. A recent study by Brunel (2017) shows that the composition of production in the EU became increasingly pollution intensive while the composition of imports became less pollution intensive over the period 1995-2008.

While there is therefore mixed evidence of pollution offshoring for the USA and EU, a broader literature has examined the potential drivers of pollution offshoring focusing specifically on the role played by international differences in environmental regulation costs.[2] The premise that firms may relocate to countries or regions with low environmental regulations or that regulations affect trade flows through changes in the competitive environment is known as the pollution haven hypothesis (PHH). As such, a growing literature has examined the link between environmental regulation costs and firms' international activities, such as exporting, importing and FDI, generally finding mixed results (see for example, Ederington *et al.* 2005; Kellenberg, 2009; Chung 2014; Rezza, 2015; Candau and Dienesch, 2017). Although recent studies have refined the methodological approach to deal with endogeneity and reverse causality issues, conclusive evidence of a pollution haven consistent effect remains elusive.[3] A related but still relatively new literature asks whether overseas outsourcing is a mechanism through which pollution offshoring takes place (Cherniwchan, 2017; Cherniwchan *et al.*, 2017; Cole *et al.*, 2017 and Li and Zhou, 2017). Outsourcing the most energy intensive and pollution intensive parts of the production process may be a way for firms to avoid domestic regulation costs or may simply be a side effect of

[1] This process of offshoring is often also referred to as the fragmentation of production (Jones and Kierzkowski 1990).
[2] The lack of evidence of pollution offshoring in the US does not of course mean that US regulations did not affect the composition of US production and imports. In the absence of stringent US regulations it is possible that the composition of production may have become less clean and the composition of imports more clean.
[3] A related literature examines the impact of exporting on the environmental performance of firms, generally finding a beneficial effect. See for example, Batrakova and Davies (2012), Cui *et al.* 2015, Girma and Hanley (2015), Holladay (2016) and Forslid *et al.* (2018).

outsourcing for more traditional economic reasons, for instance to avoid high energy, wage, or capital costs. Overseas production outsourcing typically forms a relatively small share of total imports raising the possibility that pollution offshoring through outsourcing may be diluted within, and overlooked by, studies that focus on imports. In a study of Italian firms, Antonietti *et al.* (2017) find that environmental policy stringency does increase the probability of firms outsourcing to less developed economies while Cole *et al.* (2014) find that pollution intensive, high regulation cost firms in Japan are more likely to outsource. However, to the best of our knowledge no empirical studies have provided a direct examination of the impact of international outsourcing on levels of pollution emissions or pollution offshoring.

With the above in mind, the contributions of this paper are threefold. First, this is the first paper to examine the effect of offshoring, both via importing and overseas outsourcing, on pollution emissions at the firm level. A negative relationship between importing or overseas outsourcing and emission intensity suggests the presence of pollution offshoring.[4] Second, we test whether pollution offshoring is taking place in Japan, the only industrial economy that has not experienced sharp deindustrialization. We believe that in many ways Japan represents an ideal country in which to examine pollution offshoring. The Japanese economy is the third largest in the world behind the US and China and is a mature economy with a relatively large manufacturing sector.[5] Japan also has an established network of overseas suppliers to its domestic industries via the flying geese model of global value chains so should be able to increase its reliance on these suppliers through trade or outsourcing with relative ease. Furthermore, Japanese environmental regulations are some of the most stringent and strictly enforced in the world and particularly so relative to many of its trading partners in developing Asia (Imura and Schreurs, 2005). If we expect regulations to encourage pollution offshoring then Japan is a country in which we might expect to observe this phenomenon. Third, we take a propensity score matching (PSM) and difference-in-differences (DiD) approach to examine for the first time how a firm's pollution intensity is affected by it beginning to outsource or import, utilising a unique dataset that provides information on both carbon dioxide (CO_2) emissions and offshore production for approximately 4,000 Japanese firms for the period 2009-13.

[4] Two recent studies focus on the effects of offshoring via imports alone. Cherniwchan (2017) examines the effects of NAFTA on US manufacturing plants' pollution and finds that the levels of PM_{10} and SO_2 levels are reduced due to the increased access to imported intermediate inputs from Mexico. Looking also at the US, Li and Zhou (2017) show that plants lower toxic emissions when their parent firm imports more from low-wage countries for the period 1992 to 2009.

[5] In 2016 manufacturing value added as a percentage of GDP was 21.1% in Japan, compared to 11.6% in the US and 9.0% in the UK (World Bank).

To briefly summarise our results, we find that while both the value and the carbon content of Japanese production remained relatively constant over the period 1988-2013, the carbon content did increase by 11 percentage points more than the value of production indicating that the composition of production became slightly more carbon intensive over this period. In terms of imports, the carbon content of imports grew by 415% while the value of imports grew by 325% during the same period indicating that the composition of imports became more pollution intensive, consistent with a process of pollution offshoring. This phenomenon has predominantly occurred since 2005. For the shorter period 2009-13 we find that the carbon embodied in overseas outsourcing has grown by more than the value of outsourcing again suggesting a compositional shift in outsourcing towards more pollution intensive industries. When we examine import and export patterns we find that the carbon embodied within Japanese imports is larger and has grown more rapidly than the carbon embodied within exports.

When we analyse the change in CO_2 emissions of Japanese firms that begin to outsource we find that, relative to a control group, the CO_2 emissions intensity growth rate of new outsourcing firms is 5.1 percentage points lower in the year that they start outsourcing. In the next one and two years the CO_2 emissions intensity growth rate is 6.6 and 9.5 percentage points lower than the growth rate the year before the firm started outsourcing, respectively. After decomposing firms' outsourcing activities into domestic and foreign outsourcing we find that the outsourcing effect on emission intensity growth is driven by *foreign* outsourcing with firms that start overseas outsourcing experiencing emission intensity growth that is 7.3 percentage points lower in the year they start outsourcing and 7.7 percentage points a year later compared to the year before they start outsourcing. Finally, when we investigate whether the decision to import had an impact on firm level emissions we find that firms had a lower growth rate of CO_2 emission intensity after they start importing.

The remainder of the paper is organized as follows. Section 2 examines the evidence of pollution offshoring, Section 3 outlines our econometric methodology and describes the data. Results are reported in Section 4, Section 5 tentatively considers some of the factors that may be influencing pollution offshoring and Section 6 concludes.

2. Pollution Offshoring

Our empirical analysis starts by answering the following question: how much additional pollution would have been generated in Japan if Japanese imports had been produced domestically?

Answering this question will provide an indication of how much Japanese pollution has been offshored and whether the volume of offshored pollution has increased or decreased over time. It should be noted that we are not asking how much pollution is generated overseas in the production of Japanese imports, nor are we concerned about what might be causing pollution offshoring. Our focus here is merely on the extent to which offshoring is happening.

To know how much pollution would have been generated in Japan if imports had been produced domestically we need industry specific pollution intensities which will provide the volume of pollution generated per unit of output within each industry. To construct these pollution intensities we utilise firm-level CO_2 emissions data from the Mandatory Greenhouse Gas Accounting and Reporting System provided by the Japanese Ministry of the Environment for the years 2009-2013. CO_2 emissions data are reported for all firms for whom total energy use is greater than 1,500kl per year. The CO_2 data is merged with the Annual Survey of Japanese firms and the Basic Survey of Japanese Business Structure and Activities, both provided by the Ministry of Economy, Trade and Industry.

We construct industry level pollution intensities by summing firm-level CO_2 emissions levels for each of the 11 manufacturing industries that firms are assigned to and dividing by industry-level production levels.[6] We then average over time to provide the average CO_2 intensity of each industry for the period 2009-13. Table 1 provides these pollution intensities and an immediate observation is that the most pollution intensive industries are basic metals, petroleum and coal products, and rubber and plastic products. We then multiply these CO_2 intensities by the value of Japanese imports by industry for the years 1988-2013, from the World Bank, to provide for each industry, and for each year, a measure of the CO_2 emissions that would have been generated if imports had been produced domestically.[7][8] Table 1 provides the share of manufacturing imports for each industry for 1988 and 2013 and shows the compositional changes within imports that have occurred over this period. In 2013 we can see that imports of petroleum and coal products and industrial machinery, two relatively pollution intensive industries, have both increased since 1988 and together now form over half of all manufacturing imports.

[6] Unfortunately we are limited to generating pollution intensities for only 11 industries as the firm-level data do not allow us to assign firms to more disaggregated industry classifications. We do recognize the potential shortcoming of such aggregation for representativeness.
[7] Industry level import data for Japan is from the World Bank's World Integrated Trade Solution (WITS). They are deflated using the producer price index.
[8] By using a single value of pollution intensity for each year (the average for the period 2009-13) we remove the technique effect – the effect on emissions of changing techniques of production due to regulations and technology – so that changes in emissions over time are the result of scale and compositional changes only. This allows us to ascertain the extent to which pollution offshoring is taking place.

Our industry-level measures of pollution intensity provide the pollution *directly* emitted by an industry (per unit of output) but do not capture the pollution emitted by other industries to produce that industry's intermediate inputs. When calculating the pollution intensity of imports this problem is compounded by the fact that these intermediates inputs are likely to have been produced overseas and hence won't directly feature in the import data. Levinson (2010) overcomes these difficulties by incorporating intermediate inputs using input-output tables and adjusting US pollution intensities to account for the imported fraction of each good. Unfortunately, data limitations prevent us from incorporating intermediate inputs into our analysis of Japanese emissions. However, it is worth noting that in Levinson's (2010) study of the US, adjusting for intermediate inputs made surprisingly little difference to his estimates of the pollution that would be emitted if imports were produced domestically.[9]

Figure 1 provides the results of our calculations described above. The upper two lines provide the deflated value of Japanese imports and the carbon content of those imports, both indexed so that 1988 = 100. It can be seen that over the period 1988-2013, the value of Japanese imports increased by approximately 325%. If the share of each industry in total imports remained constant over this period then the carbon content of those imports would also have grown by 325%. However, because imports by some industries grew more than others and because pollution intensities differ across industries, we actually find that the carbon content of those imports increased by 415% over this period. This tells us that the composition of Japanese imports became more pollution intensive between 1988 and 2013 or, to be more precise, the pollution that would have been emitted to domestically produce Japanese imports increased over the period. Looking more closely at Figure 1 reveals that between 1988 and 2005 the value of imports grew slightly more than the carbon content of those imports and it is only actually since 2005 that the carbon content has grown more rapidly. The effect of the 2008-09 financial crisis is clear to see although the divergence between the carbon content of imports and the value of those imports is broadly similar pre and post-crisis. Our results therefore suggest that a degree of pollution offshoring has occurred within Japan since 2005.

The lower lines in Figure 1 provide the value of production over the period 1988-2013 together with the carbon content of that production. Both have remained reasonably stable over this period relative to the growth of imports but Figure 1 does reveal that value of production has increased

[9] Of course there is nothing to say that incorporating intermediate inputs would also have very little effect in the case of Japan. But, as Levinson (2010) notes, ignoring intermediate inputs will tend to understate the pollution content of imports and if imports consist largely of finished goods then ignoring intermediates will tend to understate the offshoring of pollution.

by 13% while its carbon content increased by 24%. Again, this divergence between the two has occurred since 2005 indicating that since then the composition of domestic production has become slightly more pollution intensive.

Figure 2 performs the same exercise for overseas production outsourcing data which is available only for the shorter period of 2009-13.[10] Over this period we see that outsourcing, and its carbon content, fell before rising again although a divergence emerged between the value of outsourcing and its carbon content. Over this 5 year period the value of outsourcing increased by 15% while its carbon content increased by 24%, again indicating a compositional change towards more pollution intensive sectors.

A slightly different way to consider pollution offshoring is to use the concept of the balance of embodied emissions in trade (BEET) first introduced by Muradian *et al.* (2002). BEET is defined as:

$$BEET = EPX - EPM \quad (1)$$

Where EPX denotes the pollution embodied in exports and EPM denotes those embodied in imports.[11] A positive value indicates that there is more pollution embodied in imports than exports consistent with pollution offshoring. A similar concept to BEET is the environmental terms of trade (ETT), defined by Muradian *et al.* (2002) and Cole (2004) as follows:

$$ETT = \frac{EPX}{EPM} * 100 \quad (2)$$

The ETT are a direct corollary of the traditional terms of trade which are said to deteriorate if export prices fall relative to import prices. The environmental terms of trade are said to deteriorate when ETT rises i.e. when the pollution embodied within exports rises relative to that embodied within imports. Conversely, the ETT falls when the pollution embodied within imports rises relative to that in exports. Finally, if the ETT takes a value of less than 100 it indicates that pollution embodied within imports is greater than that in exports.

To calculate BEET and ETT we utilise our estimates of the pollution required to domestically produce Japanese imports and calculate an equivalent measure for Japanese exports using World

[10] Overseas production outsourcing is defined as a contractual relationship between a Japanese firm and an overseas firm in which the overseas firm produces a bespoke input for the Japanese firm's production process.
[11] The pollution embodied in exports is estimated by multiplying the value of exports for each industry by the CO_2 intensity for that industry.

Bank export data. These provide our measures of the pollution embodied within imports and exports.

BEET and ETT for the period 1988-2013 are shown in Figure 3. With regard to BEET, we see that it has been positive, with the exception of a few years in the 1990s, and has risen throughout the period aside from 2008-09 during the financial crisis. This indicates that the pollution content of imports has been consistently higher than that of exports and this difference has notably increased over the period. Similarly, we see that the ETT has been consistently below 100, again aside from a few years in the 1990s, indicating that the pollution embodied within imports is greater than that in exports, and has fallen steadily over time. Again this indicates that the pollution content of imports has increased relative to that of exports. In sum, we find consistent evidence to suggest that Japanese pollution offshoring is occurring and has increased, particularly over the last decade of our sample.

3. Methodology and Data

3.1 Identification strategy

Having established that Japanese pollution offshoring has increased over our sample period we now investigate whether this has in part occurred due to the offshoring of production. More specifically we ask how a firm's pollution intensity is affected by its decision to begin overseas production outsourcing /importing. We are not concerned with the factors that may have caused a firm to begin overseas outsourcing /importing or what, if any, role is played by international differences in environmental regulations. Rather, we would simply like to know if firms are offshoring the most pollution intensive parts of their production processes, thereby lowering these firms' average pollution intensity.

Estimating the effects of outsourcing or importing on firm environmental performance requires a strategy that can isolate the impact of outsourcing or importing from any other factors that might also affect firm environmental performance. Our identification strategy is to use a control group of firms that never outsource or import relative to the treatment group of new outsourcers or importers under the common trend assumption, i.e., the control group will account for other time-varying factors that would have led the treatment group to experience different performance after the treatment.[12]

[12] Examining the extent to which treatment and control group performance trends were similar in the pre-treatment period reveals a parallel trend one period before the treatment for both groups and the two lines diverge following the treatment.

In this paper, we employ a propensity score matching (PSM) and difference-in-differences (DiD) approach to examine how a firm's pollution intensity is affected by it beginning to outsource / import. PSM method has been widely adopted in studies on various subjects (Heckman *et al.* 1997; List *et al.*, 2003; Sianesi, 2004; Huttunen, 2007; Liu and Lynch, 2011; Fowlie *et al.*, 2012; Lechner and Wunsch, 2013; Elliott *et at.*, 2016). We now briefly introduce our econometric method.

We define y_{it} as firm *i*'s CO_2 emissions intensity in period *t*.[13] The statistics of our interest, the average treatment (outsourcing /importing) effect *s* period(s) later ($s \geq 0$) since the treatment on CO2 intensity is given as

$$E\left[y^1_{i(t+s)} - y^0_{i(t+s)} \middle| START_{it} = 1\right] = E\left[y^1_{i(t+s)} \middle| START_{it} = 1\right] - E\left[y^0_{i(t+s)} \middle| START_{it} = 1\right]$$

where the superscript denotes the treatment and $START_{it}$ is a dummy which equals one when firm *i* starts the treatment. The crucial problem is that $y^0_{i(t+s)}$, emissions intensity of firm *i* at $t+s$ had it never had the treatment since *t*, is unobservable. Following Rosenbaum and Rubin (1983) and Heckman *et al.* (1997), we apply PSM to find an appropriate control group by selecting firms that have never participated in outsourcing /importing as close as possible to those firms that start such activity in terms of its predicted propensity to start outsourcing / importing. We assume that firms that are similar in terms of observable characteristics are also similar in terms of unobservable characteristics. The PSM is useful here to mitigate the observable and unobservable characteristics that are correlated with the choice to offshore. If we have a balance on the observables, it is more likely that we have a balance on the unobservables (Altonji et al., 2005).

The probability of starting to outsource or import is estimated by:

$$P(X) = Pr(START_{it} = 1|X) = \Phi(X_{i(t-1)}, D_j, D_t) \quad (7)$$

where *P* denotes the propensity of firm *i* to start outsourcing/importing at time *t*, and $\Phi(.)$ is the normal cumulative distribution function. *X* is a vector of firm characteristics including age (*logage*), size (*logemp*), average employee wages (*logwage*), labour productivity (*logLP*), export activity (*logexp*), import (*logimp*)/outsourcing activity(*logOS*), foreign ownership (*FOR*), R&D activity (*RD*) and foreign direct investment activity (*FDI*) following the literature on determinants of firm-level outsourcing/importing strategies (Mol, 2005; Tomiura, 2005; Cusmano,2010; Arvanitis and Loukis,

[13] We focus on CO_2 intensity rather than total emissions as lower emission intensity means that less pollution is being produced per unit of output.

2013; Capasso *et al.*, 2013 and Kasahara and Lapham,2013).[14] A full set of industry dummies (D_j) and year dummies (D_t) are also included to capture industry and time effects respectively.[15] All time-variant explanatory variables are lagged by one year in order to mitigate bi-directional causality concerns. Furthermore, we include the pre-treatment growth of CO_2 emissions intensity (*pregrowth*) in the estimation.[16] The propensity scores are estimated by Probit since the treatment *START* is binary..

After creating a balanced propensity score, we match each outsourcing/importing starter with firms from the control group.[17]

We adopt kernel matching method and matching is done with different bandwidths and replacement and common support .[18] [19] Rather than matching across the entire manufacturing sector, our matching is performed within each 2-digit-sector-year group. In this way we create control groups within narrowly defined industries in the same year. This is important as firms in different industries face different technological and market conditions and the propensity to start outsourcing or importing of these firms may differ substantially between different industries. Similarly, if matching is not done within the same year, an outsourcing/importing starter in the treatment year can be matched with a control firm in any year.[20] We then perform several balancing tests between the treated and control groups of the matched sample to ensure the matching is of good quality (see Rosenbaum and Rubin, 1985; Flury and Riedwyl, 1986 ; Smith and Todd, 2005; Caliendo and Kopeinig, 2008 and Austin, 2009 for more discussion). Having constructed a good quality matched sample, we then use a difference-in-differences (DiD) method to estimate the effect of outsourcing/importing on emissions intensities. The advantage of a combined PSM-

[14] We are unable to estimate firm level total factor productivity (TFP) due to a lack of information on firm-level intermediate inputs and so rely on a simple measure of labour productivity measured as output per worker.

[15] We also use interactions of industry and year dummies instead as robustness checks and results are identical in terms of sign and significance.

[16] It is important to include pre-treatment growth as it is possible that firms that start treatment were already on a permanently different growth rate of CO_2 intensity (either higher or lower) than those firms that never outsource. Failing to control this could result in this difference mistakenly capturing the decision to start treatment.

[17] See Dehejia and Wahba (2002), Imbens (2004) and Garrido *et al.* (2014) for more details on balancing tests on the estimated propensity scores of both groups.

[18] Several matching algorithms are available, see Stuart (2010) for a review of propensity score matching and Austin (2013) for a comparison of 12 different algorithms for matching on the propensity score. Kernel matching is shown to maximize precision as more information is used than with other matching algorithms as the sample size is maintained because only observations outside the range of common support are discarded (Garrido *et al.*, 2014).

[19] See Chiu (1991), Silverman (1998), Sheather (2004), Caliendo and Kopeinig (2008) and Garrido *et al.*, (2014) for more discussion on bandwidth selection.By imposing common support, new starters whose propensity scores are higher than the maximum or lower than the minimum of those in the control group are dropped.

[20] In practice we create a number of bins for each 2-digit sector-year combination and assign each observation to a bin. Matching is then performed within each of the bins depending on the estimated propensity scores of each observation.

DiD is that it improves the accuracy of the estimates as we are able to control for common shocks and time-invariant unobserved firm characteristics.

Our PSM-DiD estimator based on a sample of matched firms is given by $\frac{1}{N_T}\sum_{i\in T}[\Delta y_{i(t+s)} - \sum_{j\in C} w_{ij}\Delta y_{j(t+s)}]$,

where *T(C)* denotes the treatment (control) group, N_T is the number of firms in the treatment group on the common support, *t* is the time period when treatment occurs$\Delta y_{i(t+s)}$ and $\Delta y_{j(t+s)}$ are the differences in emission intensities between *s* periods ($s \geq 0$) after treatment at *t* and pre-treatment period (*t*-1) for firms in the treated group and control group respectively, i.e., $\Delta y_{i(t+s)} = y^T_{i(t+s)} - y^T_{i(t-1)}$ and $\Delta y_{j(t+s)} = y^C_{j(t+s)} - y^C_{j(t-1)}$, and w_{ij} is the weight placed on the matched control firm *j* when constructing the counterfactual estimation for treated firm *i*.

3.2 Data Description

We use CO_2 data from the Mandatory Greenhouse Gas Accounting and Reporting System, firm level data from the Annual Surveys of Japanese firms and outsourcing data from the Basic Survey of Japanese Business Structure and Activities. The datasets are matched using each firm's name and address. The merged dataset contains firms' basic information such as year of establishment, assets, employment, sales, profit, wages as well as import and export activities, outsourcing activity, R&D and FDI. After cleaning we have an unbalanced panel of 19,503 observations for the period 2009 to 2013. All nominal values are converted to 2005 prices using a GDP deflator. See Table A1 in the Appendix for detailed definitions of the variables.

Our measure of outsourcing captures the value of each firm's outsourcing of production processes (as opposed to services, training and so on) and we differentiate between domestic and overseas outsourcing.[21] Our measure of environmental performance is firm-level CO_2 emissions intensity (*co2int*) which is defined as the CO_2 emissions of a firm divided by total output and as common in the literature we use deflated sales as proxy for output as the latter is not reported in our dataset (Tomiura, 2007; Cui *et al.*, 2015; Richter and Schiersch, 2017). One way to think about how a firm's CO_2 intensity may change as a result of the decision to outsource or import is to imagine a firm that manufactures a final good that combines three intermediate inputs that are all produced by the firm. Assume that one input is relatively energy intensive and the other two intermediate inputs use little energy and hence are relatively clean. We wish to test whether firms are most likely

[21] While we know if a firm undertakes overseas outsourcing we do not know in which country or countries this outsourcing takes place.

to outsource the production of the relatively pollution intensive input, or to import it, thereby lowering the firm's overall pollution intensity. This may occur if outsourcing or importing is motivated by the desire of the firm to avoid the cost of compliance with more stringent environmental regulations or might be an unintended consequence of firms outsourcing for other reasons, for instance to reduce wage or energy costs.

Table 2 presents the summary statistics of our variables of interest for the full sample and for a range of different sub-samples. The bottom row of Table 2 shows that there is production outsourcing activity in 71.7% of our sample (column 2). Approximately 71% of our sample undertake domestic production outsourcing while only 8.5% undertake overseas production outsourcing. This clearly indicates that almost all of the 1,655 firms who outsource overseas also outsource domestically.

Comparing production outsourcers with firms that are not production outsourcers, we see that production outsourcers have lower CO_2 intensities but are broadly comparable in terms of other firm characteristics. However, if we compare foreign production outsourcers with not production outsourcers we observe quite striking differences. Foreign production outsourcers are much larger in terms of sales and employment, they are significantly less CO_2 intensive and they have higher volumes of imports and exports. They are also more likely to undertake FDI.

To enable us to present the treatment effects of outsourcing in the next section, we first need to ensure the quality of our matching procedure. Table A3 in the Appendix presents the balancing test results on Kernel matching for production outsourcing on firm's environmental performance for our main specification. Individual covariates included in the matching process between treated and control samples before and after matching are compared and tests show that differences exist in some of the covariates between the two groups before matching, but no statistical difference in the matched samples. [22]

4. Results

4.1 The impact of outsourcing on CO_2 intensity

[22] We perform balancing tests for each matching procedure in the subsequent estimations and ensure that matching is of satisfactory quality. Balancing test results for the quality of the match for other estimations and for other outcomes are not presented in the paper for reasons of space but are available from the authors upon request.

Table 3 presents our PSM-DiD results for Kernel matching procedures. Given our relatively short time period we consider changes in emission intensities for up to two years after the treatment.[23] The results in the top panel indicate a consistently negative and significant treatment effect for up to two years. The estimates show that, relative to the control group, the growth in CO_2 emissions intensity for new production outsourcing firms is 5.1% lower in the year that they start outsourcing than comparable firms that did not start outsourcing. In the first and second years after the initial outsourcing decision is made, CO_2 emissions growth is 6.6 and 9.5 percentage points lower, respectively.[24] One reason why the impact of outsourcing on CO_2 intensity increases over time relative to the control is that once a firm decides to begin outsourcing it then increases the volume of outsourcing over time.[25] Figure 4 plots CO_2 emissions intensity for our matched sample separately for outsourcers and non-outsourcers for the time periods t-2, t-1, t, t+1 and t+2. As can be seen, pre-trends of *co2int* in years t-2 and t-1 appear to be parallel for outsourcers and non-outsourcers however once outsourcing commences, the growth of CO_2 emissions intensity is lower for outsourcers than non-outsourcers.[26]

We then make a distinction between those firms that only outsource part of their production process domestically and those that outsource overseas in the middle and bottom panels of Table 3. Results show that for firms that start production outsourcing domestically only there is no significant impact on their environmental performance in the year of the treatment or in the following year. We do find a negative and significant (at the 10% level) effect two years after the decision to outsource. When we consider firms that engage in foreign outsourcing (alone or in addition to domestic outsourcing) we find that, relative to the control group, firms experience a significant reduction in the growth of CO_2 emissions with a fall of 7.3 percentage points in the year of the decision to outsource which increases to a reduction of 7.7 percentage points one year later. Our results do not show a significant effect two years after a firm starts to outsource overseas

[23] Please note that t is the year when a firm starts treatment and it is the same year for its matched control observations as stated in the Methodology that matching is performed with each industry-year group. Once t is determined, we are able to compare the outcomes for any particular period before or after the treatment.

[24] We estimate the effects using other matching methods, e.g., radius matching and nearest neighbour matching, with different specifications on bandwidths. We also try different pool of firms as controls, such as firms that never outsource and import or export. Very similar results are obtained. They are not presented but available from the authors upon request.

[25] In our sample, the average level of outsourcing for firms in period t, the year in which they begin outsourcing, is ¥3.7m, which grows to ¥4.3m in t+1 and ¥4.9m in t+2.

[26] The fact that CO_2 intensity increases over time for non-outsourcing firms may raise questions about the representativeness of our sample.

although the sample size is now rather small which reduces our confidence in the reliability of that coefficient.[27]

[Table 3 about here]

To provide greater confidence that our PSM-DiD analysis is capturing the effects on CO_2 intensity of becoming an outsourcer, we conduct placebo tests following Huber *et al.* (2013). First, from the sample of non-outsourcers we draw a random sample of firms (we choose a 10% proportion of the sample which provides a similar number of treated firms as in our main results) to be considered as production outsourcing starters and implement our PSM-DiD estimator to compare their environmental performance to the matched control firms. We simulate this process 500 times. In a second placebo test, for each firm that became an outsourcer we randomise the year in which this happened. Again, we do this 500 times. The results are presented in Table 4. As can be seen, we find no significant treatment effects from the placebo tests.

[Table 4 about here]

For a robustness check, we examine the impact of outsourcing on pollution emissions by linear regressions. Fixed-effects methods are applied and the results are presented in Table A4 in the Appendix. Since searching and contracting with other firms on outsourcing tasks involves entry costs which are likely to be reduced if a firm has outsourcing experience in the previous period (Tomiura, 2005; Görg, et al. 2008), we include the lagged outsourcing dummy in the regressions. Outsourcing is found to have a negative and significant impact on firms' CO_2 intensity in Column (1), i.e., firms that outsource have 2.7% lower CO_2 intensity compared to those don't. We then test whether such impact comes from domestic-only or foreign outsourcing in Columns (2) and (3) respectively and find no effects of domestic-only outsourcing while foreign outsourcing has a negative and significant impact.[28]

4.2 The impact of importing and exporting on CO_2 intensity

The final stage of our analysis is to consider the impact of trade on firms' CO_2 emissions intensities. Table 5 presents the PSM-DiD estimates of the association between importing, exporting and CO_2

[27] It would be interesting to look at the treatment effects for the sub-group of firms that outsourced continuously for 3 years. Unfortunately we are unable to do so due to the small number of such firms.
[28] The magnitudes of these coefficients are not directly comparable with those obtained from PSM-DiD due to the fact that all observations are pooled in the fixed-effects estimations while PSM-DiD focuses on the matched treated and control firms only. However, results from both methods show a negative and significant impact of outsourcing on firms' environmental performance.

emissions intensity. If a firm starts to import a relatively pollution intensive intermediate good for the first time that acts to substitute for the production of the same intermediate within the firm then one would expect a negative effect of importing on the growth of a firm's CO_2 intensity relative to the control group of non-importers. If a firm starts to export its final good there is little reason to expect that *in the short term*, relative to the control group of non-exporters, this will impact CO_2 emission intensity. The treatment in Table 5 is whether a firm is a new importer or a new exporter and has never previously imported or exported, respectively. The results show that new importers experience a 3.3% reduction in CO_2 intensity growth, compared to the control group, in the year of the treatment although this effect appears to be temporary. Figure 5 plots *co2int* for importers and non-importers for our matched sample. Again, pre-trends appear to be parallel but then a slight divergence is discernible from period t between the CO_2 emissions intensity growth of importers and those of non-importers.

Once again we undertake placebo tests both to randomise the untreated firms that we classify as switchers and to randomise the year in which actual importers became importers. The results in Table 6 are from 500 repetitions and show no significant treatment effects. This increases our confidence that our PSM-DiD analysis is capturing the impact on CO_2 intensity of a firm becoming an importer. Compared to the effects of outsourcing observed earlier, new importers experience smaller and shorter-lasting CO_2 intensity reductions relative to their matched control firms. In terms of exporting, we find no significant effect on firms' emission intensities when firms enter the export market and for the subsequent two years.[29]

In summary, our results indicate that beginning to outsource overseas or beginning to import are both associated with a subsequent reduction in CO_2 emissions intensities. The results suggest that overseas outsourcing is a more important part of the story than international trade although our time period may be too short to capture a learning from exporting effect (Girma and Hanley, 2015; Forslid *et al.*, 2018 and Holladay, 2016) whereby over time exporting may result in improved productivity which may in turn lead to greater investment in energy saving capital.

[Table 5 about here]

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[29] The literature on exporting and environmental performance argues that there is a learning effect from exporting where exposure to international markets may lead to technological spillovers that reduce emissions. Likewise, if a firm is exporting an intermediate good that is part of the global supply chain it is possible that the company being supplied will insist of certain environmental standards being met. In the case of Japan which is both a world leading in terms of the stringency of environmental regulations and in terms of being at the technological frontier such a learning effect is less likely that for other countries.

[Table 6 about here]

5. Policy discussion of the possible drivers

Establishing a causal link between potential influencing factors and pollution offshoring is challenging and beyond the remit of this paper. However we here tentatively consider what some of those factors might be.

We first consider the role played by factor endowments. Like most high-income countries, Japan has a relatively capital intensive economy with relatively high labour costs. The factor endowment hypothesis (Antweiler *et al.* 2001, Cole and Elliott 2003) predicts that such economies will specialise in capital intensive sectors which also tend to be pollution intensive. Any decrease in the cost of labour relative to capital could therefore reduce Japan's specialisation in capital (and pollution) intensive production in favour of cleaner, labour intensive production, potentially resulting in an increase in pollution offshoring as we have observed. Figure 6 shows Japanese real wages between 2002 and 2013 which can be seen to have changed very little during this key period when pollution offshoring appears to have increased.[30] Since Japanese factor intensities will depend upon the price of Japanese factors relative to those of its competitors, Figure 6 also shows US and Chinese real wages over the period 2002-13.[31] Chinese real wages can be seen to have remained very stable much like Japanese wages while US real wages have increased by approximately 8% over this period. Despite this reduction in Japanese wages relative to those in the US, there is little to suggest that capital-labour costs have been the primary driver of pollution offshoring.

We next consider the stringency of Japanese environmental regulations. Japan ratified the Kyoto Protocol climate change agreement in 2002 and tackling climate change became one of the stated priorities of the Ministry of the Environment. In 2003 the Petroleum Tax was extended to cover not only petroleum and natural gas usage but also coal. The tax was equivalent to 500 Yen (approximately US $6.5) per tonne of carbon from natural gas and 1,100 Yen (approximately US $14.5) per tonne of carbon from coal. It has since been further strengthened, with revenues used to subsidise firms investing in energy conservation. In addition to the strengthening of the Petroleum Tax, Japanese air pollution laws were strengthened in 2010 and 2011 following several high profile cases in which large firms were found to have falsified their environmental reporting to the government. The penalties for breaching regulations were increased and the circumstances

[30] Japanese real wages are from the Monthly Labour Survey provided by the Japanese Ministry of Health, Labour and Welfare.
[31] US average real wages from OECD.stat (https://stats.oecd.org/Index.aspx?DataSetCode=AV_AN_WAGE). Chinese average real wages from CEIC (https://www.ceicdata.com/en/china/real-wage-index).

in which local authorities can order firms to amend their practices were broadened.[32] Japanese environmental regulations are some of the most stringent and effectively enforced in the world, particularly relative to those in developing Asia, and there is some evidence that such regulations have strengthened since the early 2000s. However, it is also the case that environmental regulations of Japan's competitors have become more stringent, not least in China, and so the impact of Japanese environmental regulations on its competitiveness remains unclear.

A final factor that may have influenced the composition of industry within Japan over the period of our analysis is changing energy costs. An industry's CO_2 intensity will be very highly correlated with the intensity of its use of fossil fuel energy and so CO_2 intensive industries will be most affected by a rise in energy costs. Data from the Japanese Ministry of Internal Affairs and Communications show that electricity prices fell slowly from 1990 only to rise after the 2011 Great East Japan earthquake and tidal wave, which resulted in several nuclear and conventional power plants going offline, and by 2013 were almost identical to 1990 levels.[33] In contrast, gas prices increased steadily over this period and by 2013 were 39% higher than 1990 levels. Figure 6 provides Japanese fuel and electricity costs as a share of manufacturing shipments for 2002-2011 and shows these have increased steadily over this period.[34] For comparison, Figure 6 also provides fuel and electricity costs as a share of manufacturing shipments for the USA which did not exhibit the same increase over this period..[35] While we were unable to find comparable fuel and electricity cost data for China, the China Energy Group (2016) reports that real wholesale electricity costs in China fell consistently over the period 1998-2014.There is therefore some evidence to suggest that rising energy costs could have influenced the observed pollution offshoring over the period of our analysis.[36]

[32] Cole *et al.* (2013) examine the impact of environmental regulations on firm level CO_2 emissions in Japan.

[33] Since the 2011 Great East Japan earthquake occurred in the middle of our 2009-2013 analysis of outsourcing firms, we examine the effect of outsourcing on CO_2 intensity for the period prior to the earthquake. A PSM-DiD analysis is not possible due to the shortened time period but OLS estimates of the effect of production outsourcing on CO_2 intensity find a negative, significant effect for individual samples consisting of 2009 only, 2010 only, 2011 only, 2009-2010 and 2009-2011. We therefore have some confidence that our econometric findings in Tables 3 and 4 are not being driven by the effects of the earthquake.

[34] Data from Lu (2014).

[35] Sato and Dechezleprêtre (2015) also observe a 33% increase in energy price indices constructed by four key types of fuel carriers (electricity, gas, coal and oil) covering 12 industrial sectors between 2001 and 2011 for Japan while this energy price for the US in 2001 was almost identical to that of 2011.

[36] Saussay and Sato (2018) test the link between FDI and energy prices and find that foreign investments are attracted to regions that have lower energy prices using firm-level M&A data covering 41 countries between 1995 and 2014.

6. Conclusions

In this paper we examine the extent to which pollution offshoring has occurred within Japan over the period 1988-2013. We find evidence to suggest that the composition of production has become more pollution intensive over this period. Regarding imports, we find that the carbon content of imports grew by 415% between 1988 and 2013 while the value of those imports grew by just 325%. This has predominantly occurred since 2005. Again, this suggests that the composition of imports has become more pollution intensive. We also find that the pollution embodied within Japanese imports was greater, and grew more rapidly, over this period than the pollution embodied in exports. The evidence therefore suggests that Japan has been offshoring pollution over the period 1988-2013.

We then consider the extent to which this pollution offshoring has been driven by Japanese firms outsourcing part of their production processes overseas. Specifically, we investigate whether the pollution intensity of a Japanese firm falls, or grows more slowly, once it begins to outsource overseas, consistent with the firm having outsourced a relatively pollution intensive part of its production process. Using a PSM-DiD approach we investigate whether firms that start to outsource in a given year experience a reduction in their CO_2 emissions intensity in the year they start outsourcing and in the following two years in comparison to the year before they started outsourcing. Our results show that outsourcing does appear to reduce the emissions intensity for all firms in the year of outsourcing and the following years. When we make the distinction between firms that domestically outsource and those that engage in foreign outsourcing we find that domestic-only outsourcers experience no significant decrease in emissions intensities in the year of the treatment and the following year relative to the control group of non-outsourcers. However, we do find that foreign outsourcers experience a significant decrease in emissions intensity. For this group of firms the CO_2 emissions growth rate is 7.3% and 7.7% lower than the treatment group in the year of outsourcing and the following year relative to the control group of non-outsourcers. We also find that firms that begin importing experience a lower growth rate of CO_2 intensity compared to firms that do not but no such effect is found for firms that begin exporting.[37]

While an analysis of the factors that may have influenced Japanese pollution offshoring is outside the remit of this paper, it would appear that the compositional changes to Japanese imports are different to those experienced by the US or the EU (Levinson, 2009; Brunel, 2017). This suggests that the factors driving these changes to Japanese imports are likely to be domestic in nature or, at

[37] We restrict our analysis to CO_2 due to a lack of firm-level data on other pollutants such as nitrogen dioxide or sulfur dioxide.

the very least, specific to the overseas markets in which Japan operates most intensively. We provide some tentative evidence to suggest that Japanese energy costs have increased during our sample period and particularly relative to those of the US. This may have provided an incentive for firms to outsource overseas the most energy (and hence CO_2) intensive parts of their production process. The role played by environmental regulations is unclear.

From a policy perspective one could argue that Japan or other developed countries could encourage the development of specialist domestic firms that are able produce pollution intensive intermediate goods efficiently and at scale which could lead to an overall reduction in global pollution without the need for firms to relocate or to outsource dirty production overseas. Such a firm is also likely to require skilled workers and to use relatively advanced technologies and thus enable Japan to maintain a leading position in eco-innovation.

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Figure 1. The Value and Carbon Content of Japanese Production and Imports 1988-2013 (1988=100)

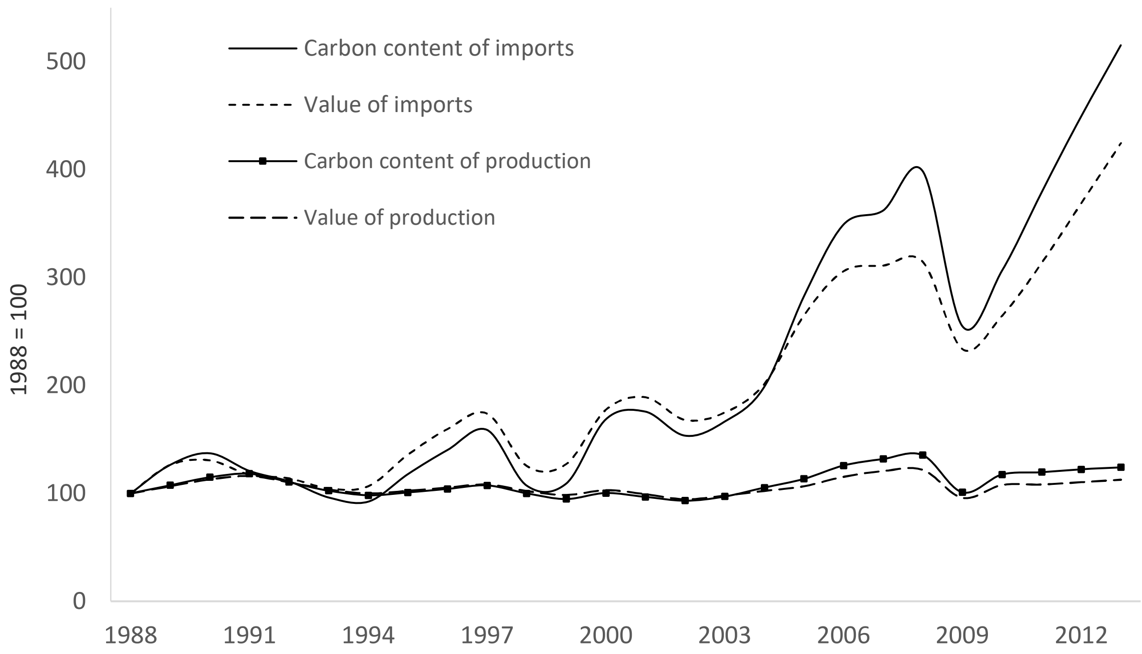

Figure 2. The Value and Carbon Content of Japanese Overseas Production Outsourcing 2009-2013 (2009=100)

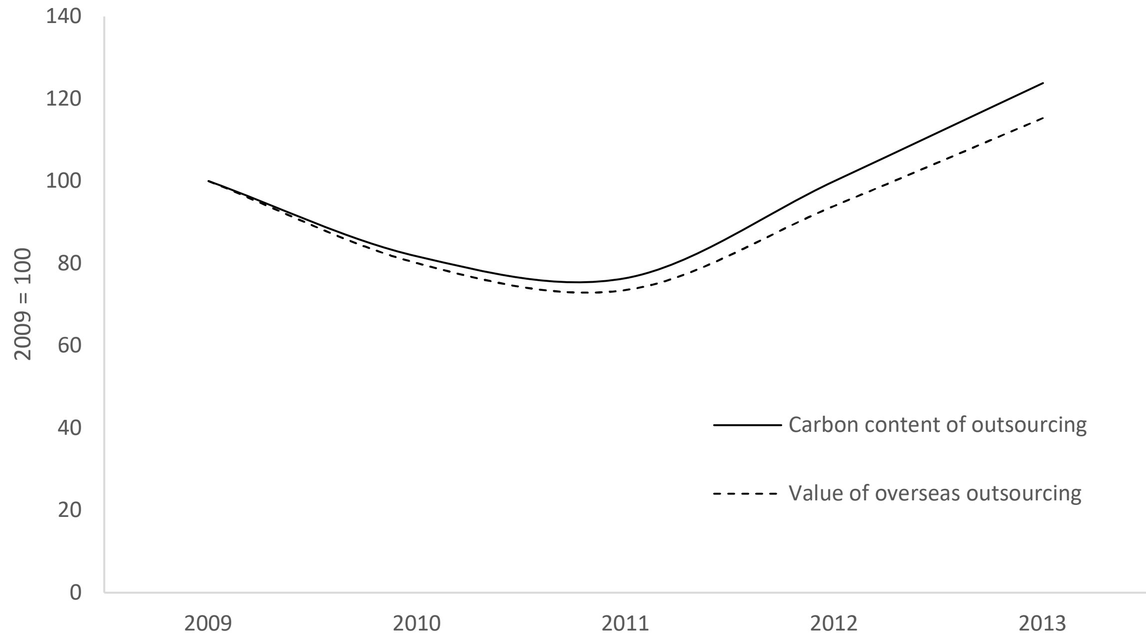

Figure 3. The Balance of Embodied Emissions in Trade (BEET) and the Environmental Terms of Trade (ETT) for Japan 1988-2013.

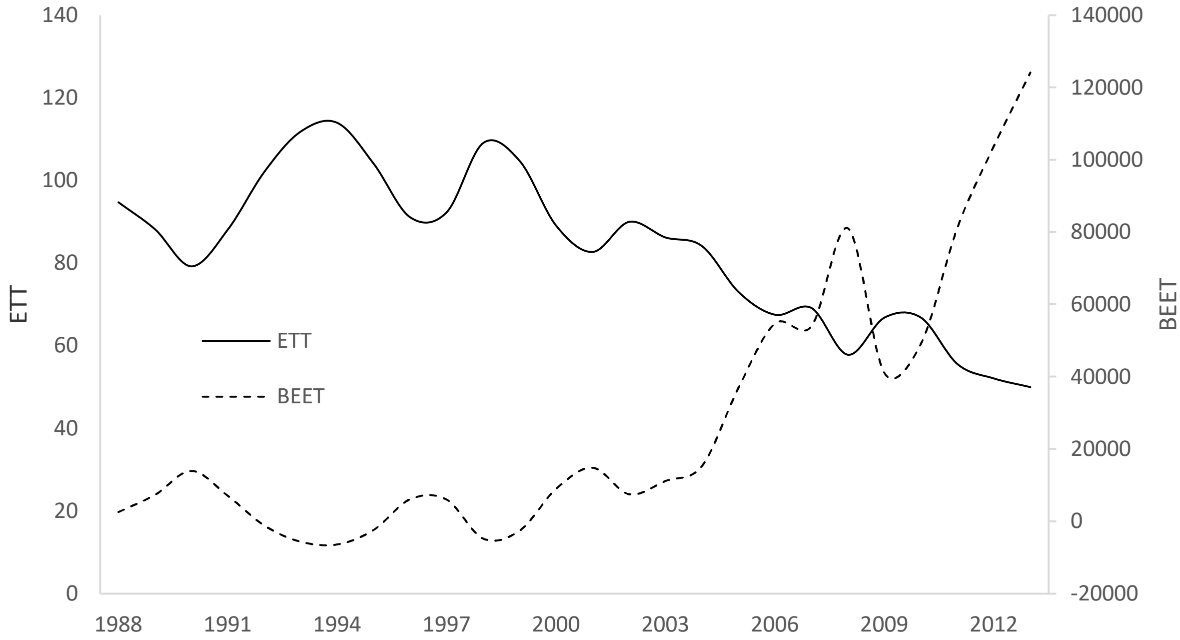

Figure 4. CO_2 intensity for outsourcers and non-outsourcers for our matched sample (where year t is the year in which outsourcing commenced for outsourcers and the same year for the matched non-outsourcers)

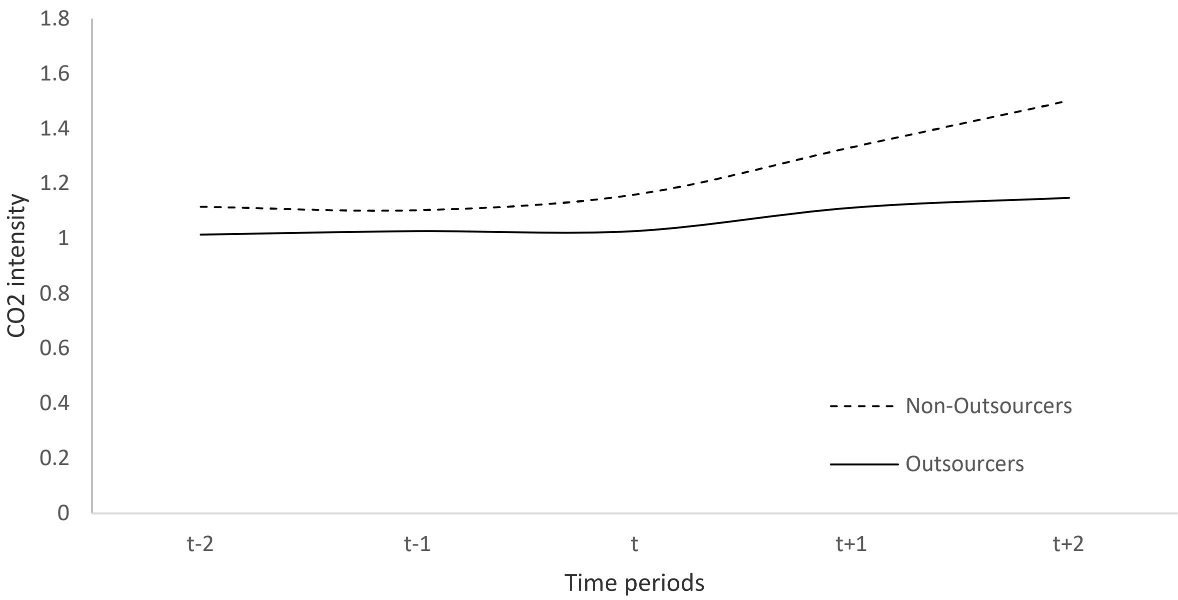

Figure 5. CO_2 intensity for importers and non-importers for our matched sample (where year t is the year in which importing commenced for outsourcers and the same year for the matched non-outsources)

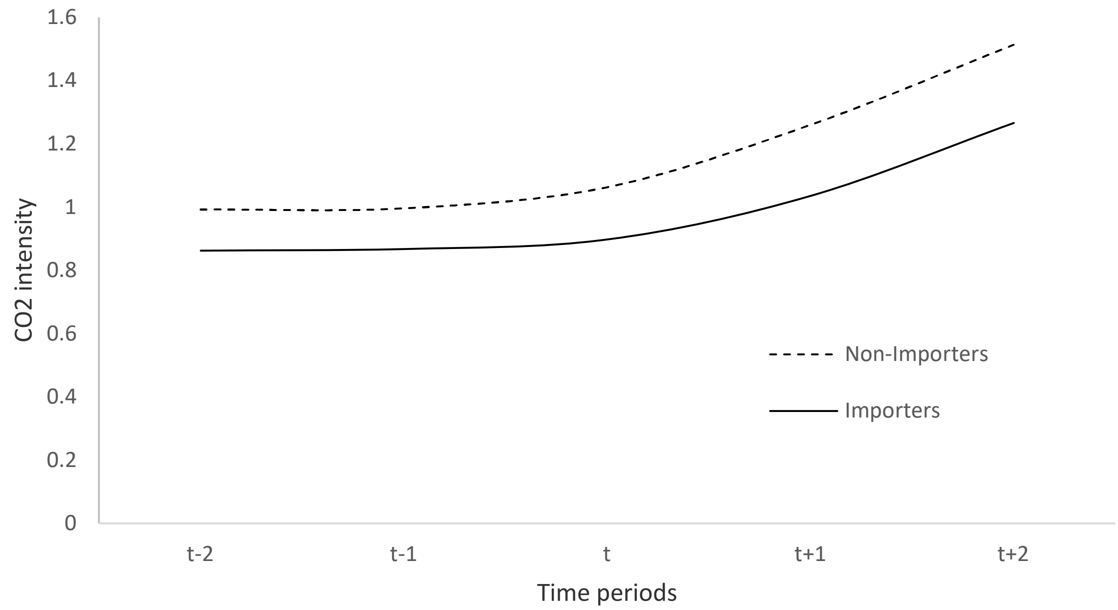

Figure 6. Trends in real wages 2002-2013 (2002 = 100) and Japanese and US fuel and electricity costs as a percentage of manufacturing shipments 2002-2011

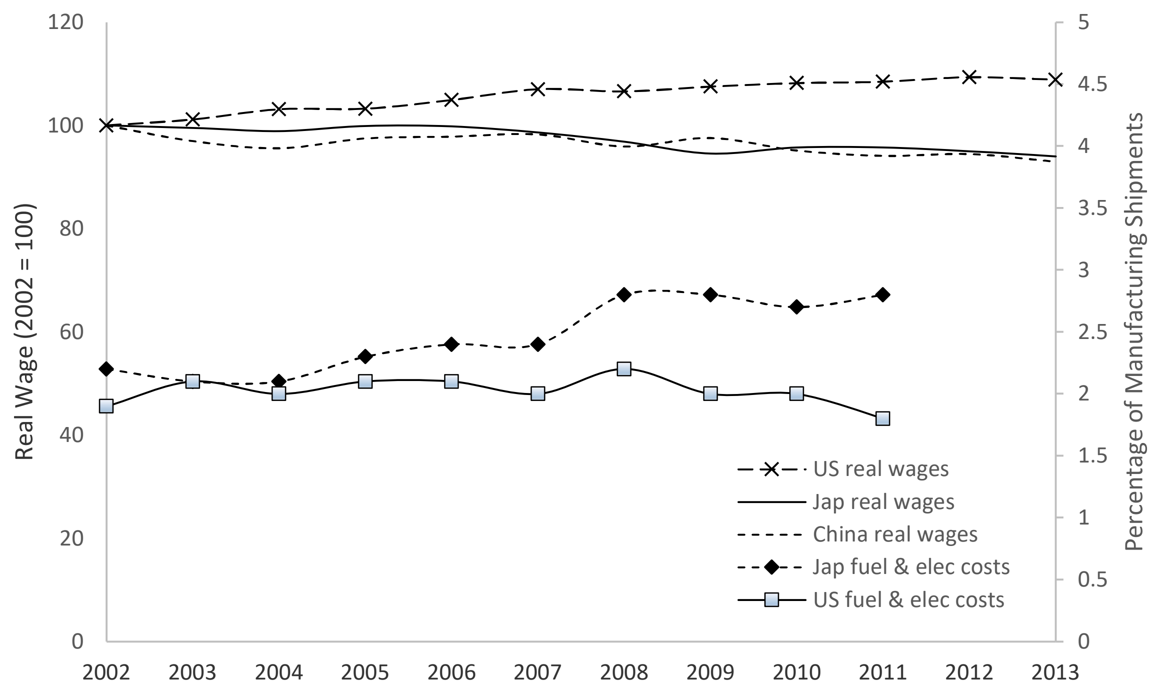

Table 1. Pollution intensities and import shares by industry

	CO_2 intensity (co2int)	Import share 1988	Import share 2013
Food and beverages	0.56	17.5	8.7
Textiles and textile products	0.70	7.2	5.0
Wood and wood products	0.76	7.3	2.3
Chemicals and allied products	0.19	7.8	8.0
Petroleum and coal products	4.75	21.5	34.3
Rubber and plastic products	2.14	2.0	2.5
Leather and leather products	1.55	1.5	0.8
Glass and ceramics	1.26	5.9	2.1
Basic metals	5.57	10.6	6.5
Industrial machinery	1.73	12.8	23.0
Other manufacturing	0.28	6.0	6.8

Table 2: Summary statistics for our key variables

Variable	(1) Full sample	(2) Production outsourcers	(3) Firms that are not production outsourcers	(4) Domestic production outsourcers	(5) Foreign production outsourcers
co2int	1.96	1.69	2.65	1.70	0.98
	(6.68)	(6.60)	(6.85)	(6.62)	(1.36)
sales	60,473	58,046	66,618	58,232	114,156
	(284,680)	(285,132)	(283,466)	(28,6074)	(592,585)
age	50.77	51.62	48.63	51.63	55.43
	(22.23)	(22.12)	(22.37)	(22.10)	(22.89)
emp	901.72	880.56	955	883	1700
	(2,792)	(2,646)	(3,131)	(2,654)	(5,028)
wage	5.38	5.46	5.18	5.45	5.75
	(2.06)	(2.09)	(1.96)	(2.09)	(1.74)
K/L	16.73	15.83	18.99	15.85	13.54
	(22.48)	(19.31)	(28.87)	(19.36)	(11.74)
LP	53.90	50.50	62.50	50.50	46.15
	(88.77)	(63.30)	(132.63)	(63.39)	(30.15)
export	12,532.00	11,902	14,131	11,938	36,394
	(127,196)	(126,540)	(128,839)	(126,968)	(318,457)
import	4,475.49	3,322	7,396	3,317	5,193
	(53,958)	(42,851)	(74,986)	(42,991)	(20,759)
FOR	0.02	0.02	0.04	0.02	0.03
	(0.15)	(0.14)	(0.19)	(0.14)	(0.17)
RD	0.60	0.63	0.52	0.63	0.79
	(0.49)	(0.48)	(0.50)	(0.48)	(0.40)
FDI	0.12	0.13	0.09	0.13	0.27
	(0.32)	(0.33)	(0.29)	(0.33)	(0.44)
Observations	19,503	13,981	5,522	13,886	1,655
% of total	100	71.7	28.3	71.2	8.5

Notes: The mean of each variable is reported with standard deviations in parentheses. See Table A1 in Appendix for definitions of the variables.

Table 3: Effects of production outsourcing on firms' CO_2 intensity (PSM-DiD estimates)

	s=0	*s=1*	*s=2*
Outsourcing			
ATT	-0.051**	-0.066*	-0.095*
	-0.026	-0.034	-0.052
N(T)	173	113	54
N(C)	1060	619	263
Domestic-only outsourcing			
ATT	-0.013	-0.025	-0.086*
	-0.025	-0.038	-0.049
N(T)	225	147	73
N(C)	1071	627	253
Foreign outsourcing			
ATT	-0.073***	-0.077*	-0.007
	-0.024	-0.041	-0.075
N(T)	114	76	31
N(C)	915	512	156

Notes: Standard errors in parentheses. *s* refers to the period(s) after the treatment. N(T) and N(C) are the numbers of observations for the treated and control groups respectively. ** and * denote significance at 0.05 and 0.1 respectively.

Table 4: Placebo tests for outsourcing (PSM-DiD estimates from 500 repetitions)

Treatment	*s=0*	*s=1*	*s=2*
Placebo Test 1. Randomise outsourcers			
	0.062	0.029	0.051
ATT	(0.050)	(0.032)	(0.049)
Placebo Test 2. Randomise year of becoming an outsourcer			
	-0.011	-0.024	-0.067
ATT	(0.028)	(0.026)	(0.042)

Notes: Standard errors in parentheses. *s* refers to the period(s) after the treatment.

Table 5: Effects of importing/exporting on firms' CO_2 intensity (PSM-DiD estimates)

Treatment	*s=0*	*s=1*	*s=2*
Importing			
ATT	-0.033*	-0.032	0.022
	(0.018)	(0.028)	(0.055)
N(T)	150	107	50
N(C)	4243	2544	1033
Exporting			
ATT	0.004	0.010	0.013
	(0.020)	(0.034)	(0.059)
N(T)	160	94	40
N(C)	4645	2529	1027

Notes: Standard errors in parentheses. *s* refers to the period(s) after the treatment.
N(T) and N(C) are the numbers of observations for the treated and control groups respectively.
* denotes significance at 0.1.

Table 6: Placebo tests for importing (PSM-DiD estimates from 500 repetitions)

Treatment	*s=0*	*s=1*	*s=2*
Placebo Test 1. Randomise importers			
	0.037	0.015	0.048
ATT	(0.044)	(0.030)	(0.049)
Placebo Test 2. Randomise year of becoming an importer			
	-0.09	-0.001	-0.010
ATT	(0.013)	(0.023)	(0.038)

Notes: Standard errors in parentheses. *s* refers to the period(s) after the treatment.

Appendix

Table A1: Definition of variables

Variable	Definition
co2int	CO_2 emission intensity of a firm which is estimated by CO2 emissions divided by real total sales
sales	a firm's annual total sales in 2005 price, in million Japanese Yen
age	a firm's age which is calculated as (survey year-foundation+1)
emp	a firm's number of employees
K/L	a firm's capital-labour intensity calculated as real tangible assets divided by the number of employees
wage	a firm's average wage of the employees
LP	a firm's labor productivity estimated as real total sales divided by the number of employees
OS	outsourcing dummy which equals one if a firm undertakes production outsourcing, 0 otherwise. Production outsourcing is defined as a contractual relationship between a Japanese firm and another domestic or overseas firm in which the domestic or overseas firm produces a bespoke input for the Japanese firm's production process.
export	a firm's total export value, in millions Japanese Yen
import	a firm's total import value, in millions Japanese Yen
exporting	a dummy variable which equals one if a firm has positive export value
importing	a dummy variable which equals one if a firm has positive import value
START	a dummy variable which equals one if a firm starts a treatment (outsourcing /importing)
FOR	foreign ownership dummy which equals one if the share of foreign capital to total capital is 50% or more, 0 otherwise
RD	a dummy variable which equals one if a firm has positive R&D expenditure, 0 otherwise
FDI	a dummy variable which equals one if a firm has one or more subsidiaries overseas, 0 otherwise

Table A2: Japanese firms' decision to start production outsourcing (Probit estimates)

Variables	(1) production outsourcing	(2) domestic-only outsourcing	(3) foreign outsourcing
pregrowth	-0.070	-0.058	0.059
	(0.059)	(0.054)	(0.073)
logage	-0.068**	-0.021	0.012
	(0.029)	(0.028)	(0.038)
logemp	-0.063***	-0.062***	-0.049*
	(0.021)	(0.019)	(0.025)
logKL	0.033	0.007	-0.037
	(0.021)	(0.020)	(0.029)
logwage	-0.133**	-0.114**	0.171**
	(0.057)	(0.054)	(0.082)
logexp	0.001	0.009	0.042***
	(0.007)	(0.006)	(0.008)
logimp	-0.008	0.014**	0.033***
	(0.007)	(0.006)	(0.008)
FOR	0.077	0.039	0.067
	(0.121)	(0.114)	(0.133)
RD	0.007	0.074*	0.174***
	(0.042)	(0.040)	(0.057)
FDI	-0.140**	-0.060	0.108*
	(0.068)	(0.058)	(0.063)
Constant	-0.642**	-1.253***	-2.123***
	(0.312)	(0.362)	(0.419)
Observations	9,689	9,689	9,393
log likelihood	-2894	-3354	-1747

Notes: Year and 2-digit sector dummies are included in all specifications. All explanatory variables except pregrowth, year and sector dummies are lagged one year. Standard errors in parentheses. ***, ** and * denote significance at 0.01, 0.05 and 0.1 respectively.

Table A3: Balancing tests before and after matching I

Variable	Unmatched Matched	Mean Treated	Control	SD	bias	t-test t	p>t	V(T)/V(C)
pregrowth	U	-0.05811	-0.00911	-17.3		-2.08	0.037	1.35
	M	-0.05811	-0.05555	-0.9	94.8	-0.08	0.939	1.32
logage	U	3.7486	3.7545	-0.9		-0.16	0.876	1.06
	M	3.771	3.8225	-7.8	-768.6	-0.77	0.442	1.24
logemp	U	5.7234	5.7416	-1.5		-0.25	0.8	0.80
	M	5.6878	5.6136	6.3	-307.1	0.57	0.567	1.11
logKL	U	2.3742	2.3587	1.6		0.27	0.79	0.92
	M	2.4439	2.3877	5.7	-262.7	0.51	0.61	0.84
logwage	U	1.5767	1.5294	11.1		1.87	0.062	0.92
	M	1.596	1.5821	3.2	70.7	0.3	0.763	0.95
logexp	U	2.6326	2.1045	14.4		2.48	0.013	1.04
	M	2.5429	2.1185	11.5	19.6	1.02	0.31	1.08
logimp	U	2.092	1.5302	17.6		3.12	0.002	1.2
	M	1.793	1.4728	10	43	0.9	0.371	1.24
FOR	U	0.04179	0.0327	4.8		0.86	0.389	.
	M	0.03425	0.02595	4.4	8.8	0.41	0.68	.
RD	U	0.58209	0.50234	16		2.74	0.006	.
	M	0.56164	0.4801	16.4	-2.2	1.39	0.164	.
FDI	U	0.0806	0.08365	-1.1		-0.19	0.85	.
	M	0.06849	0.06459	1.4	-27.7	0.13	0.894	.

Notes: Year and sector dummy variables not presented in the table but included in the balancing tests. For each of these dummies, standardized difference (SD) is 0 and p-value of t-test is 1 for the matched sample.

Table A4: Effects of outsourcing on firms' CO2 emission intensity using fixed effects methods

	(1)	(2)	(3)
VARIABLES	outsourcing	domestic-only outsourcing	foreign outsourcing
OS	-0.026***	-0.010	-0.025*
	(0.010)	(0.009)	(0.014)
L.OS	-0.012	-0.006	-0.009
	(0.009)	(0.008)	(0.014)
logage	0.182***	0.180***	0.182***
	(0.050)	(0.050)	(0.050)
logemp	-0.490***	-0.489***	-0.488***
	(0.021)	(0.021)	(0.021)
logKL	0.028***	0.029***	0.029***
	(0.010)	(0.010)	(0.010)
logwage	0.028***	0.027***	0.027***
	(0.010)	(0.010)	(0.010)
logLP	-0.766***	-0.766***	-0.766***
	(0.016)	(0.016)	(0.016)
logexp	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)
logimp	0.000	-0.000	0.000
	(0.002)	(0.002)	(0.002)
FOR	0.044	0.044	0.043
	(0.039)	(0.039)	(0.039)
RD	0.001	0.000	0.000
	(0.010)	(0.010)	(0.010)

FDI	-0.009	-0.009	-0.009
	(0.013)	(0.013)	(0.013)
Constant	4.683***	4.674***	4.654***
	(0.295)	(0.295)	(0.295)
Observations	14,170	14,170	14,170
R-squared	0.330	0.330	0.330
No. of firms	4,388	4,388	4,388

Notes: Year and sector dummies are included in all specifications. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1