The Carbon Dioxide Emissions of Firms: A Spatial Analysis

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1. Introduction

While policymakers and business leaders are increasingly aware of the linkages through which industrial production can affect the natural environment, patterns of 'environmental behaviour' continue to differ widely across firms, even when those firms reside within the same industry and country (Nakamura *et al*. 2001 and Albornoz *et al*. 2009).[1] If global environmental degradation is to be more effectively controlled, a necessary first step would seem to be to gain a deeper understanding of the causes of such cross-firm variation in emissions and other aspects of environmental behaviour.

A growing body of literature has examined the determinants of firms' environmental management practices (Henriques and Sadorsky 1996, Nakamura *et al*. 2001 and Cole *et al*. 2006) and has highlighted the roles played by a range of internal factors such as firm size and ownership structure as well as external factors, including environmental regulations, environmental lobbying and globalisation pressures. A weakness of this literature has always been the uncertain link between environmental management and actual measures of environmental performance such as emissions. A smaller body of literature has therefore attempted to directly examine measures of environmental performance, in the form of toxic air releases or local air pollution, and to identify the factors that influence them (see for example Kahn 1999, Shadbegian and Gray 2003 and Gray and Shadbegian 2004). These studies have also typically highlighted a range of factors both internal and external to the firm or plant, although data limitations have meant that this body of work focuses exclusively on the US, often concentrating on specific states or industries.

A more recent study by Gray and Shadbegian (2007) has extended the previous US environmental performance literature by allowing for the fact that the determinants of plant-level environmental performance considered in the above studies may be influenced by spatial factors. Environmental performance could be spatially correlated for a number of reasons. For instance,

[1] We use the broad term 'environmental behaviour' to encompass firms' environmental systems and policies, often referred to as environmental management, but also firms' actual environmental performance, often measured by pollution emissions.

firms and plants may be subject to location-specific environmental regulation (or enforcement) or environmental lobby groups. Additionally, industry agglomeration may result in concentrations of similar types of firms with similar levels of pollution intensity. If spatially correlated explanatory variables of this type are omitted from an econometric analysis there will be spatial dependence within the error term. The solution to this problem is normally to estimate a spatial error model in which the error term is spatially lagged. Another reason why environmental performance might be spatially correlated is if firms allow 'best practice' in pollution control to be passed between them via demonstration or imitation effects. Furthermore, if firms are subject to 'yardstick competition', and know their environmental performance is judged by consumers or regulators by making comparisons across firms, they may adjust their own environmental performance in response to that of other firms. In these two situations a firm's environmental performance is dependent on the environmental performance of other firms which necessitates the inclusion of a spatially lagged dependent variable in the estimation model.[2] Using a sample of plants based around three US cities, Gray and Shadbegian find evidence of spatial correlations in terms of regulatory compliance but not in terms of local air emissions. They suggest that a reason for the latter result may be the smaller sample of 299 plants for which toxic release data were available and 102 plants for which local emissions data were available (compared to their main sample of 521 plants).

With this background in mind, this paper examines the determinants of firms' carbon dioxide (CO_2) emissions using a unique Japanese firm-level dataset spanning the manufacturing sector. We make the following specific contributions. First, to the best of our knowledge, this is the first study to examine the determinants of firms' CO_2 emissions, despite the fact that climate change has arguably attracted more attention from policymakers in recent years than any other environmental problem. This neglect of CO_2 reflects the lack of data available for this pollutant at firm or plant-level, a limitation now remedied by our Japanese dataset. Second, again to the best of our knowledge, this is the first firm-level study of a measure of air pollution emissions for a country other than the US. Finally, for the first time, we consider the extent to which firms' emissions of CO_2 are spatially correlated.

[2] Although not explicitly considered by Gray and Shadbegian (2007), it is also possible that the characteristics of other firms may affect a firm's environmental performance. This requires the inclusion of spatially lagged explanatory variables, often in the context of the Spatial Durbin model.

The remainder of the paper is structured as follows: Section 2 provides background information on CO_2 emissions in Japan, Section 3 discusses the supply of, and demand for, pollution, the equilibrium level of pollution and possible spatial influences on pollution; Section 3 discusses data and outlines our econometric methodology: Section 4 provides our results and Section 5 concludes.

2. Background: Carbon Dioxide Emissions in Japan

Carbon dioxide is a greenhouse gas, believed to contribute to anthropogenic global warming. Although its global warming potential is the lowest of all greenhouse gases when measured on a per unit basis, because far more units of CO_2 are released compared to the other greenhouse gases, its overall warming impact is believed to the greatest (Forster *et al*. 2007). The main source of CO_2 emissions is the burning of fossil fuels. Until recently it was believed that the adverse impacts of CO_2 emissions arose entirely through its contribution to global warming, with no known local impacts. However, a recent study by Jacobson (2010) argues that the carbon dioxide domes which form over urban areas have the effect of increasing concentrations of local ozone and particulate matter, both of which have adverse effects on human health.

In 2008, Japan was the 5^{th} largest emitter of CO_2 emissions, behind China, the USA, India and Russia and was responsible for 4.01% of global emissions.[3] As Figure 1 shows, Japanese per capita CO_2 emissions appear to have stabilised in recent years although they have yet to decline.[4] Figure 1 also provides CO_2 intensity, defined as kilograms of CO_2 per US $ of GDP (in 2000 dollars), and illustrates that this has declined steadily from a peak in 1973, indicating that the Japanese economy has become more energy efficient.

[Figure 1 about here]

3 United Nations Statistics Division, Millennium Development Goals indicators (http://mdgs.un.org/unsd/mdg/Default.aspx).

4 Since population growth in Japan is close to zero total CO_2 emissions follow a very similar path to per capita emissions.

The chief contributors to Japanese CO_2 emissions are the electricity producers, followed by the Iron and Steel, Chemicals, Petroleum, Paper and Cement industries.[5] Since the share of GDP provided by many of these industries has contracted in recent years, these compositional changes will explain, in part, the falling pollution intensity in Figure 1, although environmental regulations, technological advances and greater energy efficiency more generally are also likely to have contributed.[6] We now more formally consider the factors that influence the supply of, and demand for, pollution emissions.

3. Pollution Supply and Demand

Following Pargal and Wheeler (1996) and Cole *et al*. (2005), we model pollution in terms of the supply of, and demand for, environmental services. Such services form an input into a firm's production function, with the equilibrium level of environmental services reflecting the interaction of a firm's demand for them together with the quantity that society is prepared to supply.

3.1 Pollution Demand

A number of factors are likely to determine a firm's pollution demand schedule.

Factor intensities: A firm's pollution levels are likely to be influenced by the capital intensity of its production processes. Antweiler *et al*. (1999) and Cole and Elliott (2005) demonstrate a link between the capital intensity of an industry and its pollution abatement costs per unit of value added while Cole *et al*. (2005) provide evidence of a link between the capital-labour ratio of UK industries and the pollution intensity of those industries.[7] It therefore appears that firms and industries that are heavily dependent on machinery and equipment tend to be more pollution intensive than those that are labour intensive. There may also be a link between human capital intensity and pollution intensity. Cole *et al*. (2005) find that the greater the share of value added

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[5] Japanese Business Federation.
[6] Japanese regulations aimed at tackling CO_2 emissions are discussed in Section 3.2.
[7] Antweiler *et al*. (1999) demonstrate the correlation between capital intensity and pollution abatement costs which is then utilised (though not explicitly demonstrated) by Antweiler *et al*. (2001).

paid to skilled workers in the UK the greater the pollution intensity of an industry. Although the reasons for such a link are not entirely clear, it is possible that those industries that typically generate greater volumes of pollution per unit of output are more likely to be based on complex industrial processes that require skilled labour.

Firm size: Studies such as Pargal and Wheeler (1996) and Gray and Shadbegian (2007) indicate that larger firms are typically less pollution intensive than smaller firms. This is likely to reflect economies of scale in both resource use and abatement activities. In addition, Nakamura *et al*. (2001) and Albornoz *et al*. (2009) provide evidence to suggest that larger firms are more likely to undertake environmental management practices than smaller firms, presumably reflecting the greater ability of larger firms to devote resources to such practices. A number of studies suggest that the pressure that regulators and lobby groups place on firms is likely to be a function of the firm's size. For instance, Greve (1989) argues that environmental groups are more likely to sue larger firms, irrespective of whether they are the worst polluters, simply because they are more likely to settle to avoid adverse publicity. However, in contrast, Yeager (1987) argues that government agencies are more likely to target smaller firms to prevent protracted legal battles with large firms.

Innovation: Firms that invest in research and development (R&D) are likely to benefit from product and/or process innovations. A primary or secondary benefit of process innovations will often be greater efficiency of resource use which should, other things being equal, result in fewer resource inputs and less pollution per unit of output.

Public profile: Firms with a strong public profile may be particularly concerned to appear 'green' in the eyes of the general public. Indeed, Badrinath and Bolster (1996) estimate that the main cost to firms of the environmental damage that they generate is the market penalty associated with being perceived to be environmentally damaging, a finding reinforced by Ziegler *et al*. (2007). Such a penalty is likely to be greatest for high profile, often international, firms.

Globalisation: Firms that operate in international markets may have to be more competitive, and perhaps resource efficient, than those that merely serve the domestic market, and more likely to adhere to internationally recognised environmental management practices such as ISO 14001.[8] Linked to 'public profile' above, such firms may also be particularly keen to be seen to be operating in an environmentally responsible manner. Other aspects of globalisation may also be relevant, including whether or not the firm outsources part of its production processes and whether the firm is domestically or foreign owned. In the case of outsourcing, a firm may be less pollution intensive if it has outsourced some of the dirtier parts of its production process and is now responsible only for the cleaner parts. However, if only the more pollution intensive firms outsource in this manner we may still detect a positive relationship between outsourcing and pollution intensity. Finally, with regard to foreign ownership, there is evidence to suggest that foreign-owned firms in developing countries are likely to be cleaner than domestically owned firms (Eskeland and Harrison 2003, Cole *et al*. 2008 and Albornoz *et al*. 2009) although other studies such as Huq and Wheeler (1993) and Hartman *et al*. (1997) find no such evidence. However, in a high-regulation country such as Japan we would not necessarily expect foreign ownership to significantly influence pollution intensity.

Other firms: Finally, a firm's pollution levels may be influenced by the emissions of other firms, particularly those located nearby. This may arise through demonstration or imitation effects, in much the same way as Foreign Direct Investment (FDI) and export spillovers are suggested to occur between firms (Dunning 1977, Gorg and Greenaway 2004). Such effects can occur if firms with greater knowledge or experience of pollution control demonstrate to other firms, intentionally or otherwise, the most effective methods of controlling emissions and avoiding regulation costs. Albornoz *et al*. (2009) find evidence to suggest that the environmental management practices of domestic firms are influenced by the presence of foreign firms within the firms' industry or the industries in which the firms trade. We might expect these effects to be strongest for firms that are located in the same area and/or that operate within the same industry. Furthermore, yardstick competition may cause a firm's emissions to be influenced by those of other firms if, for instance, a race to the top occurs as firms try to avoid being the target of regulators. Finally, in principle, the characteristics of nearby firms could also influence a firm's emissions. While examples of such linkages are less obvious, one example could be if the nearby

[8] ISO 14001 is an internationally recognised standard that confirms that a firm has an effective environmental management system in place.

presence of a large firm made a firm control its emissions more because it now felt it more likely that regulators would visit that location. In this situation, the size of neighbouring firms is influencing a firm's CO_2 emissions.

3.2 Pollution Supply

Environmental Regulations: Firms will face an upward sloping 'environmental supply schedule' as a result of environmental regulations. Thus, the more environmental services a firm utilises, i.e. the more pollution it releases, the greater the costs incurred by the firm.

A distinction can be drawn between formal and informal environmental regulation. The former refers to the traditional style of regulation, often in the form of pollution charges imposed by the national government, local government or environmental regulatory body. However, in situations where these formal regulations are considered by local populations to be too weak or to not satisfactorily reflect their preferences, we may see the emergence of informal regulation. This arises when local communities themselves 'regulate' local polluters through bargaining and lobbying (Huq and Wheeler 1992, Pargal and Wheeler 1996, Hartman, Huq and Wheeler 1997 and Kathuria 2007). Although originally associated with developing economies where formal regulation may be weak or absent, there is evidence that such informal regulation also occurs in developed countries (Cole *et al*. 2005). If local populations feel that formal regulations are not sufficient to protect their local environment they may lobby the regulator to increase monitoring or enforcement or may lobby firms directly. However, in principle, there may be no reason to assume that such lobbying will always be aimed at strengthening environmental regulations. If communities believe that stringent regulations may jeopardise new investment they may lobby for *reduced* stringency of regulations to try to increase their attractiveness to potential investors.

Formal environmental regulations in Japan developed in the 1960s and 1970s and prior to 2001 was governed by the Environment Agency. In 2001 the newly formed Ministry of the Environment took over this role. Recent environmental policy in Japan emanates from a major reorganization of the environmental law system that occurred in 1993 with the passing of the *Basic Environmental Law* and other related laws. These national laws cover all aspects of the natural environment including air and water emissions, energy use, solid waste emissions and recycling. Prefectures and municipalities are allowed to exceed national regulations if they wish to do so and have the flexibility to impose stringent emissions limits, the use of specific technologies or reporting and monitoring requirements. A feature of Japanese environmental policy is the large number of local agreements made between polluting firms and prefecture or municipality level authorities (Hibiki and Arimura 2004). These agreements provide regional authorities with the flexibility needed to ensure that national air pollution concentration limits are not exceeded. As a result, the regulation of firms in areas dominated by industrial production will often be more stringent than the regulation of firms in rural areas. Furthermore, if a firm fails to meet its regulations on common air pollutants such as sulphur dioxide or nitrogen oxides, the manager could face a fine of 1 million Yen (approximately US$ 13,000) or a one year prison sentence.

Having ratified the Kyoto Protocol climate change agreement, the fight against 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.

It is therefore clear that the carbon dioxide emissions of Japanese firms that form the focus of this paper will be subject to a range of formal environmental regulation, including direct climate and energy policies but also indirectly affected by regulations targeting emissions of energy-related pollutants such as sulphur dioxide and nitrogen oxides.

However, in addition to these formal regulations, there is evidence that pollution is also informally regulated in Japan. Perhaps the best known example of such informal regulation occurred in response to so-called Minamata Disease in the late 1950s and 1960s, eventually shown to be a result of mercury poisoning arising from chemical production in Minamata City. Recognition of the link between mercury emissions and Minamata Disease was only eventually accepted by the government and the responsible firms after lengthy campaigns by fishermen and other affected parties. These campaigns ultimately led to the regulation of mercury emissions in Japan. A second, more recent, example of informal regulation occurred in 2000 when a group of activists, researchers and energy specialists known as the Green Energy Law Network worked with an alliance of politicians to pass laws encouraging the use of renewable energy (Schreurs 2002).

3.3 Pollution Equilibrium

Based on the above discussion of pollution demand and supply we can now consider pollution in equilibrium to be defined as;

$$E_i = \beta X_i + \rho E_{-i} + \gamma X_{-i} + \theta Z_r + \varepsilon_i \tag{1}$$

where subscripts i and r denote firm and region, respectively, and subscript $-i$ denotes firms other than firm i. E represents CO_2 emissions intensity (CO_2 emissions per unit of output). X is a vector of firm characteristics that influence a firm's pollution demand and Z is a vector of regional variables capturing formal and informal regulatory pressures, as outlined above.

One of the contributions of this paper is to argue that firms' CO_2 emissions intensity is likely to be spatially correlated. There are several ways in which spatial correlations could influence a firm's emissions intensity (E_i) in equation (1). First, the error term ε_i may be spatially correlated due to the omission of spatially correlated explanatory variables. As Gray and Shadbegian (2007) point out, environmental regulations may be subject to local variations if, for instance, regulators apply more stringent conditions in certain areas in a bid to prevent local pollution 'hot spots'. Furthermore, plants located close to each other will share the same local characteristics such as the strength of local lobby groups which could potentially influence firms' emissions. Finally, due to agglomeration effects, we might expect firms within the same, or closely related, industries to be spatially clustered. As a result, firms in the same locale may share common characteristics such as their production processes, the age and types of technology used and, by implication, their levels of environmental performance. If any of these factors are omitted as explanatory variables then ε_i is likely to be spatially correlated. A second source of spatial correlation in equation (1) is if a firm's emissions are directly influenced by the emissions of other nearby firms, E_j, as discussed in Section 3.1 above. Finally, the term X_j in equation (1) refers to the characteristics of *other* nearby firms which themselves may influence a firm's emissions, again as discussed above.

The following section will outline the manner in which these spatial correlations are incorporated into our econometric analysis.

4. Data and Methodology

4.1 Methodology

Referring to equation (1), we initially assume that δ and σ are zero and that the error term is not spatially correlated. We estimate equation (2) using OLS.[9]

$$E_i = \beta X_i + \theta Z_r + \varepsilon_i \qquad (2)$$

Where each variable is as previously defined. The variables in vector X capture the various determinants of pollution demand discussed above. We use the capital-labour ratio (*KL*) to capture physical capital intensity and the wage rate (*WAGE*) to capture skill levels. To capture firm size (*SIZE*) we split firms into 4 quartiles according to total employment, with the first quartile (smallest firms) being the omitted category. Innovation is measured using R&D expenditure as a share of output (*R&D*) and each firm's public profile is captured using advertising expenditure as a share of output (*ADV*). To capture the various aspects of globalisation that may influence pollution emissions we include the proportion of a firm's output that is exported (*EXP*), the percentage of each firm's equity that is foreign-owned (*FOR*), whether or not the firm has undertaken FDI and owns foreign affiliates (*AFF*) and whether a firm outsources abroad (*OUT*) expressed as a share of output. Vector X also includes 24 industry specific dummy variables (with one omitted).

[9] Our sensitivity analysis explores possible endogeneity concerns.

With regard to vector Z, we do not have direct measures of formal and informal regulations. Instead, we rely on our industry dummies to capture industry specific formal regulations and argue that other aspects of formal and informal regulation are likely to be region-specific, as discussed in section 3.2 above. Vector Z therefore includes a number of variables intended to capture regional pressures on environmental regulation.

Since regulators have to ensure that national air quality guidelines are not breached, regulation is likely to be more stringent for firms operating in areas with high concentrations of manufacturing firms. Conversely, it could be argued that firms operating in areas containing high concentrations of manufacturing firms may be less 'visible' and hence may actually receive less attention from regulators. We therefore include a measure of regional manufacturing output as a share of total output to capture this effect (*MANF*). The potential health costs of pollution are likely to be greater in areas that are densely populated which may mean firms operating in such areas will receive greater attention from regulators. In addition, population density may also partially capture informal regulatory pressure since the greater the number of people in a particular area the greater the potential lobbying pressure they can exert. We therefore include regional population density (*POPD*). The stringency of a firm's regulations and the degree to which they are enforced may reflect a regional authority's priorities and the resources they are able, or willing, to devote to environmental protection. To capture these effects we include the number of officials employed within a region who are responsible for pollution control (*POLLCON*) together with regional per capita income (*INC*). The level of income in a region will reflect the social problems in that region and the extent to which pollution control is likely to be a priority of the authorities and the local population. Furthermore, more affluent populations may be more concerned about the impact of pollution on property prices and are perhaps better placed to mobilise opposition to polluters. Finally, we include two variables to capture the age distribution of the population in each prefecture. These are the proportion of the population which is greater than 65 years of age (*ELDERLY*) and the proportion of the population under the age of 16 (*CHILD*). Both the elderly and the young may be more susceptible to the health risks of air pollution although the elderly may be more politically organised and likely to vote than the young but the young may be more environmentally aware than the elderly. Each of these variables is measured at the prefecture level. Appendices A1 and A2 provide definitions of all of our variables and summary statistics, respectively.

While equation (2) provides our base model, it does not include the spatial considerations outlined in Section 3.3 above. If we have spatially correlated omitted variables and these omitted variables are independent of the included explanatory variables then OLS coefficient estimates will be unbiased but inefficient. In this situation we should allow the error term in equation (2) to be spatially correlated i.e. to depend upon the error term in neighbouring firms as follows;

$$\varepsilon_i = \lambda \sum_{j=1}^{n} W_{ij}\varepsilon_j + \mu_i \tag{3}$$

Where $\Sigma_j W_{ij}$ denotes the interaction between the error term of firm i (ε_i) and the error term of neighbouring firms (ε_j), where w_{ij} denotes the i,j element of a spatial weight matrix W (discussed below) and λ indicates the degree of spatial correlation. Since all spatial interdependence is captured by the error term, the estimated coefficients on the explanatory variables can be directly compared to those estimated using OLS.

However, if there is spatial correlation within the explanatory variables, implying that firms' emissions are influenced by the characteristics of neighbouring firms, then it is necessary to estimate a spatial explanatory variables model as defined below;

$$E_i = \beta X_i + \theta Z_r + \sum_{j=1}^{n} W_{ij} X_j \gamma + \varepsilon_i \tag{4}$$

Where W is the previously defined spatial weight matrix, X is our vector of explanatory variables γ is a vector of parameters to be estimated. The term $\Sigma_j W_{ij}\ X_j\gamma$ therefore represents spatially weighted explanatory variables. [10]

Finally, if there is spatial correlation within the dependent variable, implying firms'

[10] If equation (4) also includes the spatially lagged dependent variable ($\Sigma_j W_{ij}\ E_j$) then it is known as a spatial Durbin model. We here estimate equation (4) with and without $\Sigma_j W_{ij}\ E_j$ and find results to be very similar.

environmental performance is directly influenced by that of other firms, then a spatial lag model may be estimated, as outlined in equation (5);

$$E_i = \rho \sum_{j=1}^{n} W_{ij} E_j + \beta X_i + \theta Z_r + \varepsilon_i \tag{5}$$

Where ρ is the spatial correlation coefficient, W is the spatial weight matrix as previously defined and hence $\Sigma_j W_{ij}\ E_j$ is a spatially lagged dependent variable. Since this is now an autoregressive specification, the estimated coefficients cannot be directly compared to those estimated using OLS (or a spatial error model).

It is of course possible to combine the different spatial econometric models, for example to include both a spatially lagged dependent variable and a spatially weighted error term, often referred to as the Kelejian-Prucha model after Kelejian and Prucha (1998). Alternatively, a spatial Durbin model includes both spatially lagged dependent variables and spatially weighted explanatory variables, while the spatial Durbin error model includes spatially weight explanatory variables and a spatially weighted error term. Finally, all three possible spatial terms can be included to form a Manski model (Manski 1993). While the focus of this paper is on the models outlined in equations (3)-(5) we do also report these further models where appropriate.

It is worth noting here that a recent paper by Gibbons and Overman (2012) questions whether causal inference should be attached to estimated spatial coefficients such as ρ and γ. Gibbons and Overman argue that identification of such terms is difficult when they are included within the same model. We therefore make causal inference with a degree of caution and emphasise the fact that controlling for spatial correlations will increase the precision of the non-spatial estimated coefficients.

Our spatial analysis utilises three different inverse distance spatial weight matrices (W). First, on the basis that firms are more likely to be influenced by firms that reside within the same industry we use an industry weight matrix that weights firms in the same industry according to their physical distance and assigns zero weight to firms in different industries. Second, in case firms within the same prefecture are more influential than other firms we use a prefecture weight matrix that weights firms in the same prefecture according to their physical distance and assigns zero weight to firms in different prefectures. Finally, we use a prefecture and industry matrix which weights firms in the same industry *and* prefecture according to their physical distance and assigns zero weight to all other firms. All spatial models are estimated using maximum likelihood.[11]

Our analysis proceeds as follows. First we estimate our baseline OLS model without allowing for possible spatial correlations within our data. We then undertake several spatial correlation tests before estimating our spatial models.

4.2 Data

Our data come from the merger of two firm-level datasets. The first, entitled *Kigyou Katsudou Kihon Chousa* (The Results of the Basic Survey of Japanese Business Structure and Activities), is provided by the Research and Statistics Department, Minister's Secretariat, Ministry of Economy, Trade and Industry (METI) and contains information for 13,234 manufacturing firms. To be eligible for inclusion in this dataset, firms must have more than 50 employees and capital of more than 30 million Yen. The second dataset contains firm-level CO_2 emissions for 3,287 manufacturing firms for 2006 provided by the Japanese Ministry of the Environment. To be eligible for inclusion in this dataset, firms must consume more than 1,500 kilolitres of oil equivalent per annum.[12] We also utilise prefecture-level data provided by the Japanese Statistical Bureau in the Ministry of Internal Affairs and Communications.

After merging the firm-level datasets, obtaining co-ordinates for each zip-code, cleaning the data, and restricting the sample to contain firms from the manufacturing sector only, we are left with

[11] Appendix A3 outlines our maximum likelihood estimation procedure. The variance-covariance matrix for the estimated parameters were obtained from the second-derivatives of the log-likelihood with respect to the parameter (Anselin 1988 and LeSage and Pace 2009).

[12] These firms are required to report their CO_2 emissions to the Japanese government. Firms calculate emissions by applying 24 different emissions coefficients to 24 highly specific types of energy use and face a strict financial penalty if they do not report their emissions or if they are found to have inaccurately reported emissions.

1,961 firms for 2006.[13] Firms within this sample are distributed across all 24 two-digit manufacturing industries and all 47 prefectures. Figure 2 illustrates the geographical distribution of our firms. Appendix A4 provides a comparison of the summary statistics in the final sample of 1,961 with those in the original 13,234 for those variables common to both samples. As can be seen, firms in our final sample are on average larger in terms of total employment, have higher capital-labour ratios, more R&D and advertising expenditures and higher wages than firms in the original sample. These differences reflect the fact that our CO_2 dataset includes only firms that consume more than 1,500 kilolitres of oil equivalent per annum.

[Figure 2 about here]

4.3 Plants versus Firms

A feature of our dataset is that variables are measured at the level of the firm rather than the plant and no information is provided on the number of plants per firm. In some cases firms may be single plant firms, in other cases firms may have multiple plants, potentially distributed throughout Japan.

The implication for our spatial analysis is that the spatial co-ordinates that we have for each firm will belong to the firm's headquarters in the case of multiple-plant firms, rather than belonging to each plant. However, there are three reasons why we still might observe spatially correlated CO_2 emissions across firms. First, some firms will be single plant firms and hence we will be accurately measuring the location of those firms. Second, in the case of multi-plant firms, it will generally be the headquarters of each firm that determines the firm's environmental management practices, approves the purchasing of environmental technology and ensures that the firm is complying with environmental regulations. As a result, the spatial proximity of different firms' headquarters may be a good indicator of the strength of networks between firms and the ability

[13] Our sample falls from 3,287 to 1,961 as a result of missing observations for explanatory variables. Co-ordinates to allow us to exploit the spatial nature of our data were obtained from www.openstreemap.org. Of the 1,961 firms in our sample, 74% have unique latitude and longitude co-ordinates while the remaining 26% share co-ordinates with at least one other firm. To ensure that we accurately capture any interdependence between this latter group of firms we randomly allocate each firm to a unique co-ordinate within a 25 metre radius of their original co-ordinates.

of one firm's managers to pass on good practice to the managers of other firms. Thirdly, as discussed above, a potential cause of spatial correlation is the fact that different firms may be subject to the same regional characteristics (income, demography etc) and regional regulations. Since, in many cases, the plants within a multi-plant firm will be located within the same prefecture, not least due to agglomeration effects, these plants will be subject to the same regional characteristics. Furthermore, since we use prefecture level variables to capture the strength of regional informal regulations, our use of prefecture level variables will be appropriate if a firm's plants are located within the same prefecture.

5. Results

Column 1 of Table 1 reports the results from our baseline non-spatial OLS model. We can see that CO_2 emissions per unit of output are a positive function of the capital-labour ratio, as expected, and the wage rate. With regard to firm size, we find that medium, large and extra large firms have lower emissions intensities than small firms (the omitted category), as expected, although for extra large firms the difference is not statistically significant. So, although our sample includes only larger than average firms, we still find CO_2 intensity to be sensitive to firm size. R&D expenditure, advertising expenditure, export share and a firm having foreign affiliates are all found to reduce CO_2 intensity in a statistically significant manner.[14] Whether or not the firm is foreign-owned or outsources do not affect CO_2 intensity. For our OLS model none of the local variables are statistically significant.

[Table 1 about here]

We now begin to explore the spatial correlations in our data by performing Lagrange Multiplier (LM) tests and Moran's *I* tests on the OLS residuals and on the dependent variable (CO_2 intensity) for each of our three weight matrices. We also perform the Moran's *I* test on the explanatory variables. The results are reported in Table 2 while the tests themselves are outlined in Appendix A5. With regard to the OLS residuals, both tests indicate the presence of spatial

[14] In unreported estimations we replace the export share variable with a dummy variable indicating whether or not firms export. This was also a negative and statistically significant determinant of CO_2 intensity.

correlation with the exception of the same industry and prefecture weight matrix. Both tests also indicate the presence of spatial correlation in the dependent variable. Anselin and Rey (1991) indicate that if the spatial lag LM test statistic is greater than the spatial error LM test statistic then the former model should be chosen. Table 2 indicates that this is indeed the case, although for completeness we report both spatial error and spatial lag models. By comparing the Moran's *I* test statistics for CO_2 intensity and the OLS residuals we can see that, for the same industry weight matrix, the OLS model captures the majority of the spatial correlation within CO_2 intensity, leaving only a small test statistic for the residuals. The same is also true of the same industry and prefecture weight matrix, although the test statistic for the residuals is not statistically significant. In contrast, in the same prefecture weight matrix model, the majority of the spatial correlation remains within the residuals. Turning to the test statistics for the explanatory variables, we can see that there is spatial correlation in the majority of them. As we might expect, in the same prefecture model, where the majority of the spatial correlation remains in the OLS residuals, the test statistics for the explanatory variables are relatively small. In contrast, for the same industry and the same industry and prefecture weight matrices, where relatively little spatial correlation remains in the residuals, the test statistics on the explanatory variables are larger. In these two models, the largest spatial correlations are in *R&D* and exports (*EXP*).

[Table 2 about here]

Table 1 contains the spatial error models, for our 3 weight matrices, which can be directly compared to the OLS model. Generally, the sign and significance of the estimated coefficients are similar to those from the OLS estimation with the majority of the local variables remaining statistically insignificant. The exception is regional income in the industry weight matrix model which is found to be a negative determinant of CO_2 intensity and significant at 10%. The negative coefficient on regional income implies that more affluent regions are cleaner, as one would expect. Consistent with the Moran and LM residual tests, the spatial correlation coefficient λ is statistically significant for the industry weight matrix and the prefecture weight matrix but not for the combined industry and prefecture weight matrix.

Table 3 provides the results from our spatial explanatory variables model as provided by equation (4). It can firstly be seen that the sign and statistical significance of the non-spatial explanatory variables are very similar to those in Table 1. However, the estimated coefficients on the spatially weighted explanatory variables are almost all statistically insignificant with the exception of *ADV* in the 'prefecture' weight matrix model and, to a lesser extent, in the 'industry and prefecture' weight matrix model. This is in contrast to the Moran's *I* test result in Table 2. Table 3 also reports the results of LM tests on the residuals which show that the residuals from the prefecture, and industry and prefecture models are not spatially correlated but spatial correlation is found within the residuals for the industry weight matrix. For this weight matrix alone, a spatial Durbin error model is therefore estimated in which a spatially weighted error term is included alongside spatially weighted explanatory variables.[15] The sign and significance of our explanatory variables remain very similar to the previous results.

We also estimate a standard spatial Durbin model, containing spatially weighted dependent and explanatory variables, and a Manksi model containing spatially weighted dependent and explanatory variables and a spatially weighted error term. In all cases ρ, the coefficient on the lagged dependent variable, was not statistically significant and hence the models simplified to the spatial explanatory variables model and the spatial Durbin with error models, respectively. For reasons of space the spatial Durbin and the Manski models are not reported.

We therefore now turn to our spatial lag results. Since the estimated coefficients from a spatial lag model cannot be compared directly with those in Table 1, we report these coefficients in Appendix A6. However in the main text we instead follow LeSage and Pace (2009) and report the total impact of explanatory variable X on dependent variable E, which is the sum of the direct and indirect impacts. The direct impact (i.e. $\frac{\partial E_i}{\partial X_{iq}}$ where x_{iq} denotes the qth variable from the explanatory variable matrices) represents how changes in X_i affect E_i combined with how those changes in E_i affect E_j (i.e. other firms' emissions) and how that subsequently feeds back to E_i. The indirect impact (i.e. $\frac{\partial E_i}{\partial X_{jq}}$ where $i \neq j$) captures how X_j affects E_j and how that impact on E_j

[15] Estimating the spatial Durbin with error model for the prefecture, and industry and prefecture weight matrices provides statistically insignificant values of λ.

affects E_i. These impacts can then be directly compared with the OLS and spatial error coefficients in Table 1. Table 4 reports the total impact of each explanatory variable for our three weight matrices. Table 5 provides the direct and indirect impacts. Appendix A7 explains how the total, direct and indirect effects are computed. Table 4 also reports the results of LM tests on the residuals which indicate that spatial correlation remains in the residuals despite the inclusion of a spatially lagged dependent variable for the Industry weight matrix alone. For this weight matrix a Kelejian-Prucha model is therefore estimated which includes both a spatially lagged dependent variable and a spatially weighted error term.

[Table 4 about here]

The sign and significance of results in Table 4 are very similar to those in Table 1. The key determinants of CO_2 intensity continue to be the capital-labour ratio, firm size, R&D expenditure, advertising expenditure and exports. Regional variables are not statistically significant. Variable ρ from equation (5), which is the coefficient on the spatially lagged CO_2 intensity of other firms, is positive and statistically significant for all three weight matrices, although it is noticeably smaller in the Kelejian-Prucha model.[16] If we interpret ρ in a causal manner, a positive value suggests that when a firm reduces (increases) its CO_2 emissions, the CO_2 emissions of neighbouring firms also fall (rise). More specifically, taking the example of the prefecture weight matrix model which provides a value of ρ of 0.26, we see that a 1 unit reduction in all other firms' CO_2 intensity will reduce firm *i*'s CO_2 intensity by 0.26 units. To put this another way, if all firms start at the same level of emissions intensity, it will require a reduction in all other firms' emissions of 38.5% to reduce firm *i*'s emissions by 10%.

It is notable that the impacts of *KL*, *R&D*, *ADV* and *EXP* are all larger in the spatial lag results than in the OLS or spatial error results indicating that failing to incorporate a spatially lagged dependent variable had the effect of biasing downwards the estimated coefficients. For example, the final column of Table 4 indicates that the total effect of a unit increase in *KL* is to increase CO_2 intensity by 0.075 units, whereas the OLS result provide a coefficient of 0.060, indicating

[16] Estimating the Kelejian-Prucha model for the Prefecture, and Industry and Prefecture weight matrices, provides a statistically insignificant λ for each and a ρ with a magnitude very similar to those estimated using the Prefecture and Industry and Prefecture weight matrices in Table 4.

that the latter impact is 20% underestimated. Part of this underestimation is from the indirect effect which the OLS coefficient, which should be interpreted as a direct effect, does not incorporate. However, even when we compare the OLS coefficient with the spatial lag *direct* effect for *KL* of 0.0735 from Table 5, we still find that the OLS coefficient is underestimated by 18.4%. The degree of underestimation of the OLS coefficients for the other statistically significant variables ranges from 2.8% to 12.1%.

To illustrate the economic significance of our results, the Industry and Prefecture model from Table 4 indicates that, for example, CO_2 intensity in large firms is 1.048 units lower than in small firms. To put this in context, average CO_2 intensity within the small firms quartile is 3.25 tonnes of CO_2 per million Yen of output and hence if a firm moved from the small quartile to the large quartile, *ceteris paribus*, its emissions intensity would decline by 32%. Similarly, if the share of R&D expenditure in total output for the average firm increased by 10%, CO_2 intensity would fall by 0.029 units, equivalent to a fall of 1.62% for the average firm in the sample.[17] Generally, aside from *SIZE,* comparing a one standard deviation change in the other variables indicates that *KL* has the largest effect, followed by *R&D.*

[Table 5 about here]

Table 5 provides the direct and indirect effects from our spatial lag model. The direct effects can be compared with the spatial lag coefficient estimates provided in Appendix A6. The difference between the two reflects the feedback effects that pass through neighbouring firms back to the original firm. Taking the example of *ADV* from the 'prefecture' model, we find a direct effect of -13.445and a coefficient of -13.30 (from Appendix A6), implying a feedback effect of -0.145, equivalent to -1.05% of the direct effect. The feedback effects for the other explanatory variables are similarly small. It is noticeable that some feedback effects reinforce the direct effect, as in the case of *ADV* above, whereas others reduce the direct effect. An example of the latter would be the case of *RD* which has a direct effect of -13.007 and a coefficient estimate of -13.01, indicating a feedback effect of 0.003, equivalent to 0.71% of the direct effect.

[17] Calculated as ((12.99/(1/(0.022*0.1)))/1.80)*100 = 1.59%, where 12.99 is the estimated coefficient on *R&D*, 0.022 is the mean level of *R&D* in the sample and 1.80 is the mean level of CO_2 intensity in the sample.

Turning now to the indirect effects, these are statistically significant for *KL, SIZE MEDIUM, SIZE LARGE, R&D, ADV* and *EXP* indicating that if one of these variables changes for a particular firm, the effect is not just a change in the CO_2 intensity of that firm, but also a change in the CO_2 intensity of neighbouring firms. In all cases the indirect effect has the same sign as the direct effect. If we compare the magnitude of these with the magnitude of the direct effects we see that the indirect effects form 27.9%, 34.9% and 2.23% of the direct effects in the 'industry', 'prefecture', and 'industry and prefecture' models, respectively. [18] Therefore, the characteristics of firms within the same prefecture have the greatest impact on other firms' CO_2 intensities. In contrast, the characteristics of firms within the same prefecture and same industry have only a small impact on other firms' CO_2 intensities. This latter result is perhaps surprising but may simply reflect the more restrictive nature of the industry and prefecture weight matrix.

5.1 Sensitivity Analysis

In order to assess the robustness of our results we first consider the possibility that some of our explanatory variables are endogenously determined by CO_2 emissions intensity. For example, we might expect *WAGE* to be higher in pollution intensive firms due to the workers receiving a compensating differential (although CO_2 has no known local impact), or advertising expenditures may be higher in pollution intensive firms in order to offset any negative press attention, or pollution intensive firms may reduce their size to become less visible to regulators or lobby groups.

Although to some extent the cross-sectional nature of our dataset limits our ability to deal with endogeneity concerns, we nevertheless explore the effect of possible endogeneity. We do this by replacing our firm-level measures of *WAGE*, *ADV* and *SIZE* with industry-level measures given that there should be less concern of endogeneity between firm-level CO_2 emissions and industry-level measures of *WAGE, SIZE* and *ADV.* The results are presented in Table 6 for both spatial error and spatial lag models.[19] As can be seen, the results are generally very similar to those

[18] Within each model the indirect effects form the same proportion of the direct effects for each variable.
[19] For reasons of space the results presented in Table 6 were all estimated using the 'prefecture' weight matrix. The

estimated using firm-level measures of *WAGE*, *SIZE* and *ADV*. Industry-level *WAGE* is not statistically significant in common with firm-level *WAGE* in many models. Industry-level *SIZE* affects CO_2 in a negative and statistically significant way, again consistent with our firm-level measures of *SIZE*. Finally, industry-level measures of *ADV* are negative and statistically significant as we found for firm-level *ADV*. Since the coefficients on industry-level *WAGE* are not statistically significant we cannot meaningfully compare them with the previous findings, while SIZE is now measured as a continuous variable rather than the previous dummy variables, again making a direct comparison difficult. However, we can see that the coefficients on industry-level *ADV* are very similar in magnitude to those estimated for firm-level *ADV*, suggesting that endogeneity was not unduly influencing the latter coefficients. It is also notable that, when measuring a variable at industry-level, the sign, significance and magnitude of the other estimated coefficients, including the spatial correlation coefficients remain stable. This gives us some reassurance that our key findings, including the presence and magnitude of spatial relationships, are not unduly influenced by endogeneity concerns. In unreported estimations we also include all other explanatory variables measured at industry level. The results were consistent with those estimated using firm-level variables. Finally, again in unreported estimations, we drop a single explanatory variable at a time to assess the robustness of the remaining variables. We found no evidence of instability amongst the sign, significance and magnitude of our coefficients.

Next, we consider the possibility that more productive firms may have lower emissions but may also be larger and more likely to engage in exports. As such, our estimations may suffer from unobserved heterogeneity. A lack of data on material inputs limits our ability to estimate a comprehensive measure of total factor productivity (TFP) while the presence of *KL* in our model suggests that the inclusion of TFP alongside it may not be ideal. Nevertheless we try to address this issue by including a measure of labour productivity (*LABPROD*) defined as output per worker with the results reported in models (7) and (8) of Table 6. For both spatial error and spatial lag models *LABPROD* is negative but not significant. Its inclusion does not notably change the other estimated coefficients or the estimated spatial correlations. In unreported

results from the other weight matrices are very similar and are available upon request. In unreported estimations we also include the other explanatory variables measured at industry level. The results were highly consistent with those estimated using firm-level variables.

estimations we replace *LABPROD* with a measure of TFP estimated using capital and labour inputs alone and with a measure of the share of profits in output to capture efficiency. The results are very similar to those for *LABPROD* with the estimated coefficients on the other explanatory variables and the spatial correlations remaining stable. We do not therefore find evidence to suggest that our main results suffer from unobserved heterogeneity relating to productivity.

While we fully acknowledge that none of the above robustness exercises can formally rule out the existence of endogeneity, we believe they should provide some confidence in our results. However, a further exploration of robustness will not be possible until more data are available, including time series data. As such, this remains a task for future research.

Finally, earlier in the paper we raised the possibility that because our data are measured at firm, rather than plant, level the regional variables may not perform well for multi-plant firms. In order to assess whether this fact may partially explain the general lack of statistical significance amongst the regional variables we try dropping firms in the top quartile of employment levels from our sample on the basis that these firms are most likely to be multi-plant firms. Models (9) and (10) in Table 6 provide the results. As can be seen, the coefficients on the regional variables remain statistically insignificant and the magnitude of the spatial correlation coefficients are very similar to those in previous models. Removing the firms most likely to be multi-plant firms does not therefore affect our results.[20]

6. Conclusions

In light of the previously observed variations in environmental behaviour across firms and plants (Cole *et al*. 2006 and Albornoz *et al*. 2009) and the previous literature's emphasis on measures of environmental management rather than actual measures of environmental performance, this paper, for the first time, estimates the determinants of firms' CO_2 emissions. By using Japanese

[20] Finally, we estimate our main results using three weight matrices based purely on distance, with a weighting applied to firms within 30km, 50km and 100km of the firm in question. For reasons of space these results are not reported here and are available on request, but they are very similar to those in Tables 1, 3 and 4, providing further evidence that our results are not sensitive to the choice of weight matrix.

firm-level data this paper is also the first to estimate the determinants of firm-level air emissions for a country other than the US and the first to do so using spatial econometric techniques.

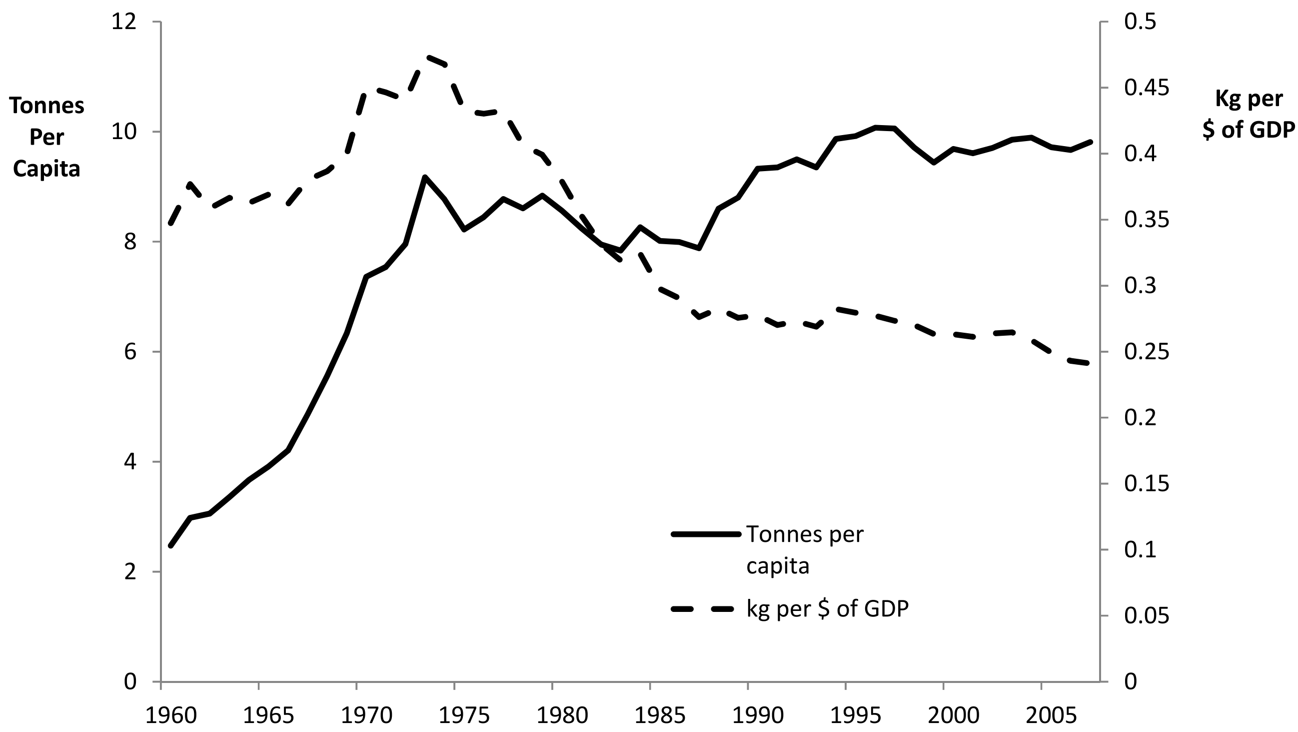
This paper finds that the key determinants of a firm's CO_2 emissions are its capital-labour ratio, its size, its R&D expenditure, its advertising expenditure (presumably reflecting the firm's public profile) and its exports as a share of output. These are important findings that aid our understanding of firms' environmental performance. For example, the strong effect of firm size in our estimations provides clear evidence that large firm release fewer emissions per unit of output than smaller firms, presumably because of economies of scale in resource use or abatement activity. Our results also indicate that investment in R&D is a useful tool to reduce emissions intensity.

Our results provide only limited evidence to suggest that local lobbying power, as captured by community characteristics, influences CO_2 emissions despite the fact that our sample contains larger than average firms that would be visible to local communities. There are several potential reasons for this lack of evidence of community lobbying, although our analysis suggests that the fact that our data are measured at the firm, rather than plant level, is not one of them. One possibility is that our inability to measure regional characteristics for geographical areas smaller than prefectures may be a partial reason for their lack of statistical significance. Studies such as Pargal and Wheeler (1996) and Gray and Shadbegian (2007) do measure community characteristics at a finer geographical level which may partially explain their stronger results for these variables, though Cole *et al*. (2005) do find significant results using data for UK regions which are broadly similar in size to Japanese prefectures. However, unlike this study, the focus of each of these prior studies was on pollutants with local impacts and hence it is possible that the communities do not lobby against CO_2 in quite the same way as they might for pollutants that are directly influencing the local environment. Finally, our findings may also suggest that national decision making is the main driver of Japanese regulations and community lobbying does not play a significant role in the formation of Japanese policy. This would contrast with findings for the UK, Bangladesh, Indonesia and Brazil for whom local lobbying has been shown to play a role in environmental policy making (da Motta 2006, Cole *et al*. 2005, Pargal and Wheeler 1996 and Huq and Wheeler 1993).

Evidence is found to suggest that firms' CO_2 emissions are spatially correlated. More specifically, our results indicate that the error terms within an OLS model are spatially correlated, perhaps because firms located close to each other are affected by similar local factors that are not being controlled for, such as agglomeration effects. We do not find spatially weighted explanatory variables to be significant determinants of CO_2 emissions but our results do suggest that there is spatial correlation within the dependent variable, CO_2 emissions, perhaps because of demonstration or imitation effects. Once such spatial correlations within the dependent variable are controlled for it is found that the marginal effects of the explanatory variables increase in magnitude, indicating that a failure to incorporate spatial correlations has the effect of biasing downwards the estimated coefficients. We also find evidence of small feedback effects, whereby a firm's CO_2 emissions affect other firms' CO_2 emissions which in turn affect the original firm's emissions, as well as indirect effects on CO_2 driven by the characteristics of neighbouring firms.

Although the precise mechanisms driving the spatial dependence of firms' CO_2 emissions remain speculative, and are undoubtedly the subject of future research, our results suggest that the activities of firms are inherently interrelated. Firms do not operate in isolation and pollution patterns are likely to be influenced by a complex mix of imitation effects, demonstration effects and competitive pressures more generally. The presence of such interrelationships implies that future attempts to econometrically estimate the determinants of firm-level environmental performance will need to accommodate these spatial correlations. Attempts to model industrial pollution patterns and their evolution over time also require an understanding of spatial interrelationships and will need to formally acknowledge that firms' emissions are inter independent. Such interrelationships also have implications for environmental policy and suggest that focusing attention on key firms may be fruitful. Indeed, encouraging best practice pollution control in prominent, well connected, firms within each region, may result in reductions in emissions beyond those firms.

Figure 1. Japanese CO_2 Emissions Per Capita and CO_2 Intensity 1960-2007



Source: World Bank World Development Indicators
(http://data.worldbank.org/data-catalog/world-development-indicators)

Figure 2. Map of Japan Showing Firms in our Sample (the White Cross Represents Tokyo).

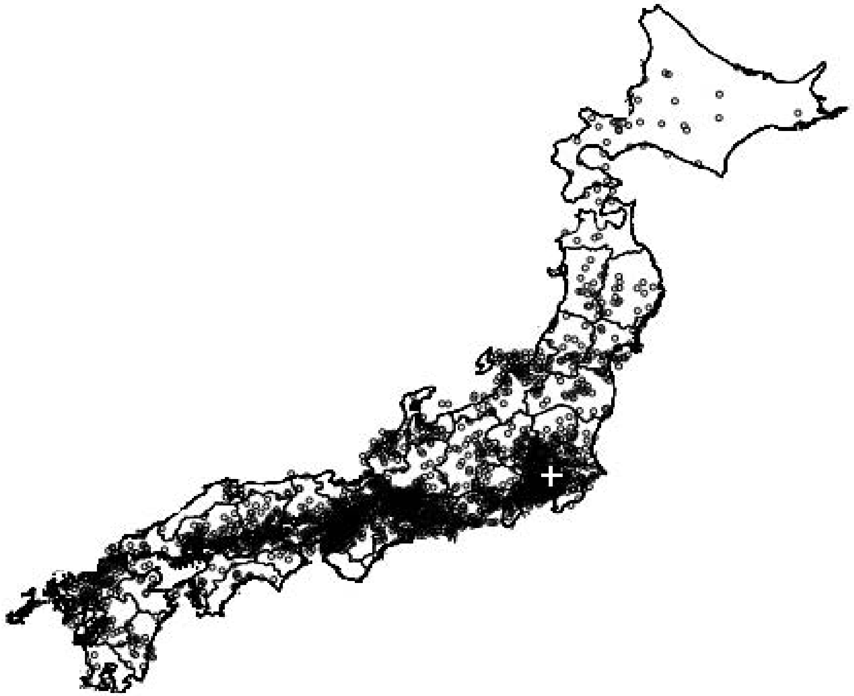


Table 1: OLS and Spatial Error Estimations (Dependent variable: CO_2 emissions per unit of output)

	Non Spatial OLS	Spatial Error Models		
		Industry	Prefecture	Industry & Prefecture
KL	0.06***	0.07***	0.07***	0.07***
	(3.51)	(5.97)	(6.14)	(5.89)
WAGE	0.08*	0.07	0.08*	0.07
	(1.94)	(1.55)	(1.79)	(1.58)
SIZE MEDIUM	-0.99***	-0.94***	-0.90***	-0.98***
	(-3.55)	(-3.86)	(-3.71)	(-4.00)
SIZE LARGE	-1.04***	-0.99***	-0.99***	-1.03**
	(-3.89)	(-3.81)	(-3.96)	(-3.95)
SIZE EXLARGE	-0.36	-0.30	-0.28	-0.36
	(-1.15)	(-1.01)	(-0.97)	(-1.12)
R&D	-13.04***	-12.95***	-12.75***	-13.09***
	(-5.56)	(-3.30)	(-3.29)	(-3.32)
ADV	-13.73***	-13.21**	-12.94*	-13.64**
	(-4.95)	(-2.01)	(-2.00)	(-2.06)
EXP	-1.10***	-1.04*	-0.96	-1.08*
	(-3.35)	(-1.66)	(1.55)	(-1.72)
FOR	-0.01*	-0.01	-0.01	-0.01
	(-1.92)	(-1.30)	(-1.10)	(-1.40)
AFF	0.002	0.02	0.06	0.01
	(0.01)	(0.08)	(0.28)	(0.04)
OUT	0.02	0.03	0.02	0.02
	(0.98)	(0.72)	(0.70)	(0.68)
POPD	-0.0002	-0.0002	-0.0004	-0.0002
	(-0.48)	(-0.35)	(-0.12)	(-0.31)
INC	-0.79	-0.88*	-1.26	-0.81
	(-0.53)	(-1.72)	(-0.38)	(-0.57)
MANF	2.28	2.39	3.22	2.25
	(0.67)	(1.03)	(1.11)	(0.93)
CHILD	5.17	2.59	-9.20	5.02
	(0.19)	(0.12)	(-0.17)	(0.20)
ELDERLY	-9.71	-9.05	-12.18	-9.66
	(-1.02)	(-1.00)	(-0.40)	(-0.95)
POLLCON	3.57	3.43	5.64	3.71
	(0.59)	(0.39)	(0.13)	(0.35)
R^2	0.21	0.22	0.23	0.21
λ	-	0.22***	0.27***	0.02
LR value dof(1)	-	1651.18**	1679.14**	1631.36**
F-test	-	14.88**	15.99**	14.02**
Observations	1961	1961	1961	1961

***, ** and * denote significance at 1%, 5% and 10%, respectively. T-statistics are in parentheses
LR test for comparison between OLS and spatial error models. F-test for combined significance
λ is the spatial correlation coefficient within the error term as defined by equation (3)

Table 2: Moran and LM tests

	Weight Matrix		
	Same Industry	Same prefecture	Same Industry and Prefecture
		LM test	
LM test on OLS residual (spatial error test)	8.59***	32.08***	0.460
LM test on CO_2 intensity (spatial lag test)	10.35***	42.47***	12.71**
		Moran I test	
CO_2 intensity	0.20***	0.12***	0.18***
OLS residuals	0.04***	0.09***	0.01
KL	0.11***	0.11***	0.16***
WAGE	0.11***	0.07***	0.13***
SIZE MEDIUM	0.01	0.02*	0.02
SIZE LARGE	0.01	0.02**	0.01
SIZE EXTRA LARGE	0.12***	0.07***	0.13***
R&D	0.26***	0.08***	0.25***
ADV	0.14***	0.03***	0.13***
EXP	0.23***	0.04***	0.22***
FOR	0.07***	0.07***	0.09***
AFF	0.08***	0.05***	0.11***
OUT	0.004	0.002	0.004

***, ** and * denote statistical significance at 1%, 5% and 10%, respectively

Table 3. Spatial Explanatory Variables Model: (Dependent variable: CO_2 emissions per unit of output)

Variable	Industry		Prefecture		Industry and prefecture		Industry (Spatial Durbin error)[3]	
	X[1]	WX[2]	X	WX	X	WX	X	WX
KL	0.08***	-0.01	0.07***	0.08	0.07***	0.03	0.06***	0.88
	(3.55)	(-0.12)	(3.44)	(0.96)	(3.29)	(0.35)	(4.8)	(0.78)
WAGE	0.09**	0.32	0.08**	0.18	0.08**	0.21	0.11**	-1.82
	(2.28)	(1.56)	(2.12)	(1.54)	(2.00)	(1.02)	(2.5)	(-0.89)
SIZE MEDIUM	-0.93***	-0.99	-0.90***	-1.19	-0.95**	-0.56	-0.84***	-0.71
	(-3.40)	(-0.96)	(-3.31)	(-1.23)	(-3.37)	(-1.17)	(-3.5)	(-0.31)
SIZE LARGE	-0.96***	-1.21	-0.91***	-0.87	-1.02***	-0.87	-0.89***	-0.83
	(-3.56)	(-1.14)	(-3.45)	(-0.92)	(-3.61)	(-1.36)	(3.5)	(-1.1)
SIZE EXLARGE	-0.25	-1.21	-0.20	-1.16	-0.33	-0.73	-0.16	-0.24
	(-0.77)	(-1.49)	(-0.61)	(-0.94)	(-0.95)	(-0.95)	(-0.55)	(-0.16)
R&D	-12.67***	1.68	-12.81***	-7.01	-12.66**	8.96	-11.5***	-2.4
	(-5.51)	(0.13)	(-5.39)	(-0.44)	(-5.11)	(0.67)	(-3.02)	(-0.19)
ADV	-14.14**	-26.20	-12.60**	-74.42***	-14.20**	-11.31*	-13.24**	-1.20
	(-5.03)	(-1.41)	(-4.32)	(-2.96)	(-5.17)	(-1.78)	(-2.09)	(-0.84)
EXP	-1.14***	-1.87	-1.01***	-1.37	-1.26*	-1.86	-1.12*	3.02
	(-3.36)	(-1.50)	(-2.96)	(-0.75)	(-3.46)	(-1.06)	(-1.82)	(1.5)
FOR	-0.01*	-0.02	-0.01	-0.02	-0.01*	0.01	-0.006	-9.2
	(-1.74)	(-0.97)	(-1.14)	(-1.35)	(-1.82)	(0.29)	(-1.0)	(-0.4)
AFF	0.01	-0.59	0.03	-1.09	0.01	-1.14	0.16	-11.11
	(0.08)	(-0.82)	(0.25)	(-1.32)	(0.08)	(-1.38)	(0.75)	(-0.87)
OUT	0.03	-0.04	0.03	0.14	0.02	-0.13	0.031	3.79
	(1.01)	(-0.51)	(0.99)	(0.70)	(0.97)	(-1.53)	(0.90)	(0.20)
POPD	-0.0002		-0.0002		-0.0001		-0.054	
	(-0.48)		(-0.42)		(-0.35)		(-1.16)	
INC	-0.91		-1.03		-0.91		-0.40	
	(-0.61)		(-0.68)		(-0.61)		(1.3)	
MANF	2.36		2.82		2.41		-0.98	
	(0.69)		(0.83)		(0.71)		(-1.12)	
CHILD	2.94		0.81		4.88		0.63	
	(0.10)		(0.03)		(0.17)		(0.70)	
EDERLY	-10.17		-9.71		-9.28		-9.78	
	(-1.08)		(-1.04)		(-1.02)		(-0.80)	
POLLCON	3.53		3.03		2.82		8.96	
	(0.59)		(0.54)		(0.49)		(0.56)	
R^2	0.21		0.21		0.22		0.28	
λ							0.15**	
LM test on residuals	6.99***		0.56		3.24			
Observations	1961		1961		1961		1961	

***, ** and * denote statistical significance at 1%, 5% and 10%, respectively

[1] X refers to the non-spatially weighted explanatory variables

[2] WX refers to the spatially weighted explanatory variables from equation 4

[3] The Spatial Durbin Error model includes a spatially weighted error term

Table 4. Spatial Lag Results: Total Impact (Dependent variable: CO_2 emissions per unit of output)

	Industry	Prefecture	Industry & Prefecture	Industry (Kelejian-Prucha)[1]
KL	0.094***	0.093***	0.075***	0.063***
	(5.87)	(5.60)	(5.94)	(4.75)
WAGE	0.095*	0.105*	0.076	0.099**
	(1.68)	(1.72)	(1.61)	(2.09)
SIZE MEDIUM	-1.239***	-1.244***	-1.009***	-0.88***
	(-3.92)	(-3.76)	(-4.01)	(-3.55)
SIZE LARGE	-1.314***	-1.342**	-1.048***	-0.95***
	(-3.81)	(-3.76)	(-3.97)	(-3.53)
SIZE EXLARGE	-0.423	-0.439	-0.358	-0.18
	(-1.08)	(-1.02)	(-1.18)	(-0.56)
R&D	-16.637***	-17.542***	-13.279***	-11.72***
	(-3.30)	(-3.24)	(-3.16)	(-3.07)
ADV	-17.270**	-18.127**	-13.849**	-13.00*
	(-2.02)	(-1.98)	(-2.05)	(-1.94)
EXP	-1.345*	-1.286	-1.117*	-1.03
	(-1.68)	(-1.60)	(-1.77)	(1.56)
FOR	-0.011	-0.010	-0.009	-0.0059
	(1.38)	(-1.15)	(-1.47)	(-0.87)
AFF	0.014	0.049	-0.005	0.16
	(0.05)	(0.17)	(-0.02)	(0.73)
OUT	0.031	0.032	0.026	0.032
	(0.70)	(0.67	(0.72)	(0.91)
POPD	-0.0003	-0.0003	-0.0002	-0.00024
	(-0.50)	(-0.63)	(-0.54)	(-0.62)
INC	-1.048	-1.495	-0.846	-1.06
	(-0.56))	(-0.72)	(-0.54)	(-0.69)
MANF	2.954	4.208	2.413	2.77
	(0.51)	(0.66)	(0.51)	(0.58)
CHILD	5.165	-5.603	4.990	-6.87
	(0.13)	(-0.12)	(0.15)	(-0.21)
ELDERLY	-11.997	-14.495	-10.128	-11.18
	(-1.23)	(-1.38))	(-1.24)	(-1.43)
POLLCON	4.164	5.662	3.782	3.74
	(0.55)	(0.68)	(0.60)	(0.62)
ρ	0.22***	0.26**	0.20**	0.045***
λ				0.10***
R^2	0.20	0.22	0.21	
LR value dof(1)	1652.88**	1690.60**	1633.46**	
F-test	14.95**	16.35**	14.04*	
LM test on residuals	9.63***	0.15	0.81	
Observation	1961	1961	1961	

***, ** and * denote statistical significance at 1%, 5% and 10%, respectively.

ρ is the spatial correlation coefficient defined in equation (6)

[1] The Kelejian-Prucha model includes both a spatially lagged dependent variable and a spatially weighted error term

Table 5: Spatial Lag Results: Direct and Indirect Impacts (Dependent variable: CO_2 emissions per unit of output)

	Direct Impacts			Indirect Impacts		
	Industry	Prefecture	Industry & Prefecture	Industry	Prefecture	Industry & Prefecture
KL	0.073^{***}	0.069^{***}	0.073^{**}	0.021^{***}	0.024^{***}	0.002^{***}
	(5.87)	(5.70)	(5.94)	(5.84)	(4.53)	(5.93)
WAGE	0.074^{*}	0.078^{*}	0.074	0.021^{*}	0.027^{*}	0.002
	(1.68)	(1.72)	(1.61)	(1.68)	(1.66)	(1.62)
SIZE MEDIUM	-0.969^{***}	-0.923^{***}	-0.987^{***}	-0.271^{**}	-0.321^{***}	-0.022^{**}
	(-3.922)	(-3.77)	(-4.01)	(-3.91)	(-3.38)	(-3.99)
SIZE LARGE	-1.027^{***}	-0.996^{***}	-1.025^{***}	-0.287^{***}	-0.347^{***}	-0.023^{***}
	(-3.81)	(-3.79)	(-3.97)	(-3.80)	(-3.36)	(-3.95)
SIZE EXLARGE	-0.331	-0.326	-0.350	-0.092	-0.113	-0.008
	(-1.08)	(-1.02)	(1.18)	(-1.078)	(-1.00)	(-1.18)
R&D	-13.005^{***}	-13.007^{***}	-12.990^{***}	-3.631^{***}	-4.536^{***}	-0.290^{***}
	(-3.30)	(-3.27)	(-3.16)	(-3.30)	(-2.96)	(-3.16)
ADV	-13.500^{**}	-13.445^{**}	-13.547^{**}	-3.770^{**}	-4.682^{*}	-0.302^{**}
	(-2.02)	(-1.98)	(-2.05)	(-2.02)	(-1.92)	(-2.04)
EXP	-1.054^{*}	-0.95	-1.093^{*}	-0.294^{*}	-0.331	-0.024^{*}
	(-1.68)	(-1.59)	(-1.77)	(-1.68)	(-1.55)	(-1.77)
FOR	-0.009	-0.007	-0.009	-0.002	-0.003	-0.0002
	(-1.38)	(-1.15)	(-1.47)	(-1.38)	(-1.125)	(-1.47)
AFF	0.011	0.036	-0.005	0.003	0.012	-0.0001
	(0.05)	(0.17)	(-0.02)	(0.05)	(0.16)	(-0.02)
OUT	0.024	0.024	0.025	0.007	0.008	0.001
	(0.70)	(0.62)	(0.72)	(0.70)	(0.66)	(0.72)
POPD	-0.0002	-0.0003	-0.0002	-0.0001	-0.0001	-0.0001
	(-0.50)	(-0.63)	(-0.54)	(-0.50)	(-0.63)	(-0.05)
INC	-0.820	-1.109	-0.827	-0.229	-0.386	-0.018
	(-0.56)	(-0.72)	(-0.54)	(-0.56)	(-0.71)	(-0.54)
MANF	2.309	3.117	2.361	0.645	1.091	0.053
	(0.51)	(0.66)	(0.51)	(0.51)	(0.65)	(0.51)
CHILD	4.037	-4.142	4.88	1.13	-1.462	0.110
	(0.13)	(-0.12)	(0.15)	(0.13)	(-0.12)	(0.15)
ELDERLY	-9.378	-10.75	-9.908	-2.62	-3.741	-0.221
	(-1.23)	(-1.38)	(-1.24)	(-1.23)	(-1.35)	(-1.24)
POLLCON	3.255	4.208	3.700	0.909	1.453	0.082
	(0.55)	(0.68)	(0.60)	(0.55)	(0.68)	(0.59)

Table 6: Sensitivity Analysis (Dependent variable: CO_2 emissions per unit of output)

	1	2	3	4	5	6	7	8	9	10
Variable	Spatial Error	Spatial Lag	Spatial Error	Spatial Lag	Spatial Error	Spatial Lag	Spatial Error	Spatial Lag	Spatial Error	Spatial Lag
KL	0.07^{***}	0.10^{***}	0.07^{***}	0.09^{***}	0.07^{***}	0.10^{***}	0.094^{***}	0.094^{***}	0.08^{***}	0.09^{***}
AveWAGE	0.37	0.65								
WAGE			0.08^{*}	0.10^{*}	0.07	0.09	0.090^{*}	0.094^{**}	0.07	0.11
AveSIZE					-0.02^{**}	-24.43				
SIZE MEDIUM	-0.88^{***}	-1.22^{***}	-0.90^{***}	-1.25^{***}			-1.34^{***}	-1.38^{**}	-0.97^{***}	-1.29^{***}
SIZE LARGE	-0.96^{***}	-1.31^{***}	-1.01^{***}	-1.38^{***}			-1.72^{***}	-1.76^{**}	-1.01^{***}	-1.36^{***}
SIZE EXLARGE	-0.26	-0.41	-0.31	-0.48			-1.07^{***}	-1.11^{***}		
R&D	-11.86^{***}	-16.10^{***}	-13.16^{***}	-18.44^{***}	-11.48^{***}	-16.21^{***}	-13.69^{***}	-13.63^{***}	-12.54^{***}	-18.61^{***}
AveADV			499.63^{*}	504.9^{**}						
ADV	-12.93^{**}	-18.06^{**}			-13.28^{**}	-18.81^{**}	-15.22^{**}	-15.71^{**}	-8.88^{**}	-11.82^{**}
EXP	-0.97	-1.36	-0.89	-1.08^{*}	-0.96	-1.33	-1.71^{**}	-1.80^{***}	-0.97	-1.33^{*}
FOR	-0.01	-0.01	-0.01	-0.01	-0.004	-0.01	-0.0036	-0.0043	-0.01	-0.01
AFF	0.07	0.06	0.05	-0.002	0.02	0.003	0.010	-0.0011	-0.35	-0.49
OUT	0.03	0.04	0.03	0.02	0.03	0.04	0.016	0.017	0.02	0.03
LABPROD							-0.0024	-0.0025		
POPD	-0.0003	-0.0003	-0.0004^{*}	-0.0002	-0.0003	-0.0003	-0.00067	-0.00056	-0.001	-0.001
INC	-1.22	-1.37	-1.33	-0.90	-1.60^{***}	-1.91	-1.15	-1.11	-0.22	-0.05
MANF	3.38	4.49	3.28	2.27	3.60	4.67	2.36	2.83	-2.13	-3.04
CHILD	-9.30	-5.02	-7.81	6.94	-15.43	-12.40	-2.60	-1.078	-2.35	-11.03
ELDERLY	-11.81	-13.88	-12.32	-9.86	-13.37	-16.29	-12.81	-11.90	-13.90	-15.75
POLLCON	5.22	4.90	5.59	3.70	4.91	4.58	10.42	8.94	7.54	7.16
λ	0.23		0.27^{***}		0.27^{***}		0.27^{***}		0.27^{***}	
ρ		0.26^{***}		0.20^{***}		0.26^{***}		0.26^{***}		0.26^{***}
R^2	0.20	0.22	0.23	0.21	0.22	0.21	0.23	0.21	0.21	0.21
Observations	1961	1961	1961	1961	1961	1961	1961	1961	1470	1470

All models use the 'prefecture' weight matrix. ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively.
λ and ρ are the spatial correlation coefficients from equations (5) and (6), respectively.

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Appendix A1: Variable Definitions

Variable	Definition
CO_2 intensity	Tonnes of CO_2 per million Yen of output
SIZE SMALL	1st quartile of firms in terms of total employment, ranging from 50-233 employees
SIZE MEDIUM	2nd quartile of firms in terms of total employment, ranging from 234-470 employees
SIZE LARGE	3rd quartile of firms in terms of total employment, ranging from 471-1032 employees
SIZE EXLARGE	4th quartile of firms in terms of total employment, ranging from 1033-78200 employees
EXP	The share of total output that is exported
KL	Physical capital stock per worker
R&D	R&D expenditure as a share of output
FOR	Percentage of equity that is foreign owned
ADV	Advertising expenditure as a share of output
WAGE	The annual wage rate per worker (million Yen)
AFF	A dummy variable = 1 if a firm has foreign affiliates
OUT	Foreign outsourcing as a share of output
LABPROD	Labour productivity, defined as output per worker
POPD	Thousands of people per square kilometre in each prefecture
INC	GDP per capita (in hundreds of Yen) in each prefecture, logged
MANF	Share of manufacturing output in total output in each prefecture
ELDERLY	Proportion of the population 65 or older in each prefecture
CHILD	Proportion of the population under the age of 16 in each prefecture
POLLCON	Number of prefecture, city and town hall officers who are responsible for pollution and environmental protection in each prefecture, scaled by area (in square kilometres)

Appendix A2: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
CO_2 intensity	1961	1.80	4.016	0.0029	69.50
SIZE SMALL	1961	0.25	0.43	0	1
SIZE MEDIUM	1961	0.25	0.43	0	1
SIZE LARGE	1961	0.25	0.43	0	1
SIZE EXLARGE	1961	0.25	0.43	0	1
EXP	1961	0.090	0.16	0	0.97
KL	1961	5.23	7.43	0.022	97.32
R&D	1961	0.022	0.027	0	0.25
FOR	1961	5.26	14.57	0	100
ADV	1961	0.0053	0.015	0	0.21
WAGE	1961	6.23	2.061	0.47	26.06
AFF	1961	0.31	0.46	0	1
OUT	1961	0.23	2.46	0	85.68
LABPROD	1961	55.24	64.43	5.52	1383.05
POPD	1961	1.47	1.82	0.00056	4.13
INC	1961	8.12	0.22	7.62	8.41
MANF	1961	0.13	0.061	0.045	0.24
ELDERLY	1961	0.20	0.023	0.16	0.27
CHILD	1961	0.13	0.013	0.11	0.19
POLLCON	1961	3.91E-07	2.02E-07	1.38E-08	7.54E-07

Appendix A3: Maximum likelihood Estimation of spatial models:

Let us define X=[X_i Z_r] to be *nxk* explanatory variables that includes both firm (*i*) and region (*r*) specific variables. Y denotes the *nx1* vector of CO_2 emission intensities.

The full log-likelihood function can be written as:

$$lnL = -\left(\frac{n}{2}\right)\ln(\pi\sigma_e^2) + \ln|I_n - \lambda W| - \frac{e'e}{2\sigma_e^2}$$

where $e = (I_n - \lambda W)(Y - X\beta)$ for the spatial error model. We estimate the coefficients by first deriving regression residuals from an OLS estimation and we then search for the value of λ that maximises the log likelihood function above, conditional on the least square estimated value $\hat{\beta}_{OLS}$ and $\widehat{\sigma_{eOLS}^2}$. Finally we update the value of $\hat{\beta}_{MLE}$ and $\widehat{\sigma_e^2}$ conditional on the value of $\hat{\lambda}$ estimated. This would be counted as one pass and the process continues until convergence is achieved in the residuals.

Similarly, the full log-likelihood function for the spatial lag model can be written as:

$$lnL = -\left(\frac{n}{2}\right)\ln(\pi\sigma_u^2) + \ln|I_n - \lambda W| - \frac{u'u}{2\sigma_u^2}$$

Where $u = Y - \rho WY - X\beta$ with $\rho \in (\min(\omega)^{-1}, \max(\omega)^{-1})$ and ω denotes the eigenvalue from weight matrix W. We first perform OLS for the model $Y = X\beta_o + u_o$ and $WY = X\beta_L + u_L$ and derive the residuals, where $u_o = Y - X\widehat{\beta_o}$ and $u_L = WY - X\widehat{\beta_L}$. Next we find the value of ρ that maximises the concentrated likelihood function below:

$$lnL_C = -\left(\frac{n}{2}\right)\ln(\pi) + \ln|I_n - \lambda W| - \left(\frac{n}{2}\right)\ln\left(\frac{1}{n}\right)(u_o - u_L)'(u_o - u_L)$$

Finally, given $\hat{\rho}$ that maximises the concentrated likelihood function, Anselin (1988) shows $\hat{\beta} = (\widehat{\beta_o} - \hat{\rho}\widehat{\beta_L})$ and $\widehat{\sigma_u^2} = (\frac{1}{n})(u_o - \hat{\rho}u_L)'(u_o - \hat{\rho}u_L)$.

Appendix A4: A Comparison of Summary Statistics

Variable	Sample used in this paper		Full sample[1]	
	Obs	Mean	Obs	Mean
SIZE	1,961	727	13,234	384
KL	1,961	5.23	13,234	4.35
R&D	1,961	0.022	13,234	0.017
ADV	1,961	0.0053	13,234	0.0038
WAGE	1,961	6.23	13,234	4.89

[1] From *Kigyou Katsudou Kihon Chousa* (The Results of the Basic Survey of Japanese Business Structure and Activities)

Appendix A5 Moran and Lagrange Multiplier Tests

Moran I test

Moran's I is the most widely used test for possible spatial dependence in error of regression model. Let ϵ_{OLS} denotes the regression residual from an OLS regression[21]. The Moran I statistic can be written as:

$$I = \epsilon'_{OLS} W \epsilon_{OLS} / \epsilon_{OLS}{}' \epsilon_{OLS}$$

The asymptotic distribution of the standardised Moran's I statistics follows a standard normal distribution. The mean and standard deviation can be written as:

$$E(I) = tr(MW)/(n-k)$$

and $V(i) = [tr(MWMW') + tr(MW)^2 + \frac{(tr(MW))^2]}{d} - E(I)^2$ where $d = (n-k)(n-k+2)$ and $M = (I - X(X'X)^{-1}X')$.

The standardised Moran I statistics can be written as:

$$Z_I = [I - E(I)]/V(I)^{1/2}$$

where a value statistically different from zero indicates spatial dependence. A positive value indicates positive spatial dependence whilst a negative value indicates negative spatial dependence.

Lagrange Multiplier (LM) test

With the same notation as in Moran I test above, the LM test provides an alternative way to test for possible spatial dependence in the error term of a regression. The test statistics can be written as:

$$LM = \left(\frac{1}{T}\right)[\epsilon'_{OLS} W \epsilon_{OLS}) / \sigma^2_{OLS}]^2 \sim \chi^2(1)$$

where $T = tr(W + W') * W$. The test statistic follows a chi-square distribution with 1 degree of freedom. A value that is significantly different from zero indicates spatial dependence in the error.

[21] To test for possible spatial correlation in dependent and explanatory variables, we first regress the variable in question against only an intercept term using OLS.

Appendix A6 Spatial Lag Estimation Coefficients (Dependent variable: CO_2 emissions per unit of output)

Variable	Industry	Prefecture	Industry & Prefecture
KL	0.07^{***}	0.07^{***}	0.07^{***}
	(5.93)	(5.65)	(5.89)
WAGE	0.07	0.08^{*}	0.07
	(1.63)	(1.73)	(1.60)
SIZE MEDIUM	-0.97^{***}	-0.91^{***}	-0.99^{***}
	(-3.96)	(-3.78)	(-4.01)
SIZE LARGE	-1.03^{***}	-0.99^{***}	-1.04^{***}
	(-3.96)	(-3.85)	(-3.97)
SIZE EXLARGE	-0.35	-0.33	-0.36
	(-1.15))	(-1.10)	(-1.21)
R&D	-12.84^{***}	-13.01^{***}	-13.06^{***}
	(-3.28)	(-3.36)	(-3.31)
ADV	-13.50^{**}	-13.30^{**}	-13.67^{**}
	(-2.06)	(-2.04)	(-2.07)
EXP	-1.07^{*}	-0.97	-1.09^{*}
	(1.71)	(-1.56)	(-1.72)
FOR	-0.009	-0.007	-0.009
	(-1.38)	(-1.15)	(-1.41)
AFF	0.01	0.033	0.01
	(0.06)	(0.16)	(0.03)
OUT	0.02	0.02	0.02
	(0.67)	(0.70)	(0.68)
POPD	-0.0002	-0.0003	-0.0002
	(-0.53)	(-0.64)	(-0.55)
INC	-0.83	-1.10	-0.81
	(-0.56)	(-0.71)	(-0.54)
MANF	2.29	3.13	2.23
	(0.51)	(0.67)	(0.49)
CHILD	4.07	-3.89	5.22
	(0.13)	(0.12)	(0.16)
ELDERLY	-9.29	-10.72	-9.67
	(-1.22)	(1.39)	(-1.26)
POLLCON	3.52	4.11	3.70
	(0.59)	(0.70)	(0.62)
ρ	0.22^{***}	0.26^{**}	0.02^{**}
	(98.02)	(9.86)	(52.23)
R^2	0.20	0.22	0.21
LR value dof(1)	1652.88^{**}	1690.60^{**}	1633.46^{**}
F-test	14.95^{**}	16.35^{**}	14.04^{*}
Observation	1961	1961	1961

Appendix A7. Calculating Total, Direct and Indirect Impacts in the Spatial Lag Model

Due to the spatial correlation in the dependent variable (ρ), changes in the explanatory variable in one firm affect the average CO_2 emission of other neighbouring firms in other locations. This means that the interpretation of the impact from the explanatory variables are not represented by the estimation coefficients (β) (Kim *et al.* 2003, Anselin and LeGallo 2006 and LeSage and Pace 2009). Instead, they are a combination of the coefficients (β and ρ) and the spatial weighting matrix (W). It can be written as:

$$\frac{\partial E_i}{\partial X_{iq}} = (I_n - \rho W)^{-1} I_n \beta_{1q}$$

where X_{iq} indicates the *qth* explanatory variable in X_i for individual firm i and β_q indicates the estimated coefficients for the variable X_{iq}. LeSage and Pace (2009) develop a method to calculate the impact and their inferences based on a simulation of the normally distributed parameters (β_q, ρ and σ^2). The effect of the independent variables on the dependent variable is called the total impact. There are $n*q$ such effects, one for each explanatory variable X_{iq} and observation i. The average effect over all observations is represented by the average total effect calculated from $n^{-1}\iota_n'[(I_n - \rho W)^{-1} I_n \beta_{1q}]\iota_n$.

The average direct impact is calculated as $n^{-1}tr[(I_n - \rho W)^{-1} I_n \beta_{1q}]$ that represents the average response of the dependent variable to the independent variables plus the feedback effect from firm i to all the other firms then back to itself. The average indirect effect is the difference between the average total and average direct impact. It represents the average externality of the explanatory variable from/to neighbouring firms.

The dispersion of the impacts was estimated with Bayesian Markov Chain Monte Carlo (MCMC) methods as in LeSage and Pace (2009).