Environmental Regulation and Innovation: An Empirical Study on K-REACH and CCA

By

MIN, Soyeon

THESIS

Submitted to

KDI School of Public Policy and Management

In Partial Fulfillment of the Requirements

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Committee in charge:

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ABSTRACT

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By

MIN, So Yeon

This paper investigates the impact of K-REACH and CCA on innovation, based on the "weak" version of the Porter Hypothesis (PH), using both panels of manufacturing industries and firms in South Korea during 2011-2018. In 2015, South Korea newly enforced two stringent chemical regulations, the K-REACH and CCA to protect public health and the environment from chemical disasters. Given there are only very few relevant studies, our analysis will be the first attempt to examine the PH that a well-crafted environmental policy induces innovation activities of firms. Our empirical results are based on sequential adoption of the quasi-experimental method of Propensity Score Matching (PSM) and the Difference in Differences (DID) estimation as well as a standard panel regression. With the innovation activities being measured by R&D expenditure, the number of patent applications, entry rate of new firms and exit rate of existing firms, we find no evidence to support the PH.

Keywords: K-REACH, CCA, Porter Hypothesis, toxic chemicals, environmental regulation, innovation, difference-in-differences, propensity score matching

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Most importantly, my special appreciation goes to my family; Yeongseob Min, my father, Giyoung Lee, my mother and Jeongwoo Min, my brother for giving me their love and warm hearts, always. My three-month research journey would not be possible without their invaluable supports.

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1. Introduction

Whenever stringent environmental regulations newly come out, there has been always a heated debate over their effects on competitiveness. A standard viewpoint on the link between environmental regulation and competitiveness is that strong legislation for environment protection increases industrial compliance and production costs, and thus weakens economic competitiveness in the end. Reversely, Porter (1991) and Porter and van der Linde (1995) challenge the traditional paradigm by asserting "a properly crafted environmental regulation can trigger innovation offsets as a win-win strategy that may partially or fully offset the complying costs", so-called the Porter Hypothesis (PH).

The PH is further specified into three distinct variants (Jaffe & Palmer, 1997). First, the "narrow" version of the PH states that a certain type of environmental policy such as outcome-based regulations provides innovation incentives to firms compared to prescriptive policies. Second, the "weak" version of the hypothesis argues that a well-designed environmental policy stimulates innovation since firms will behave differently with new constraints to their profit-maximizing due to the regulation. Finally, the "strong" version posits that a new environmental policy consequently enhances productivity, since it may induce firms to seek a new way that both comply with the regulation and increase profits.

Chemical substances, meanwhile, can adversely affect not only human health but also the environment. Given the potential chemical hazards, introducing a chemical regulatory system around the world started from the US Toxic Substances Control Act (TSCA) in 1997, followed by the EU's Registration, Evaluation, Authorization and Restriction of Chemicals (REACH) in 2007 and Japan's Chemical Substances Control Law (CSCL) in 2010. Above all, the EU's REACH regulation was a big turning point for international trade markets of chemicals to make the ‘no data, no market’ formula, which legally stops any transaction of firms if they cannot prove that their distributed chemicals are not harmful.

In 2015, South Korea joined the international regulatory movements by newly enforcing two stringent chemical regulations, Korea's Act on the Registration and Evaluation, etc. of Chemical Substances (K-REACH) and Chemicals Control (CCA), aimed to reduce using hazardous chemicals and encourage firms to produce environment-friendly chemical substances. In particular, South Korea has seen a series of chemical disasters in recent years; Gumi, where a massive leakage of hydrofluoric acid gas killed five people in 2012, the humidifier disinfectant case in 2013, the worst chemical incident with 1,553 people killed until now, and most recently, toxic chemical leak of LG chemical factories happened again in 2020. A train of the tragic chemical incidents considerably alerted the country to enact the two stringent chemical regulations not only to protect public health by opening information-access to the public about chemical substances firms use in their products but also to reduce chemical accidents and minimize the deadly effects to the environment with pre-management on chemical facilities.

On the industrial side, however, complaints about the chemical regulations have grown. In 2019, under Japan’s tightened restrictions on exports to Korea, with semiconductor companies not being able to import their main Japanese-produced components, an issue of the technical gap between Korean and Japanese materials-industries started to be raised. Many firms now argue that the increased complying burdens caused by the regulations let competitiveness in Korean-materials industries behind the counterpart country. Therefore, the two chemical regulations have big political importance, given they should achieve their regulatory purposes for protecting the health and the environment as well as not losing industrial competitiveness.

In this paper, we investigate the impact of the two environmental regulations on innovation activities in South Korean manufacturing sector. Since the K-REACH and CCA are not market-based regulations, we estimate the impact based on the weak version of the hypothesis, not the narrow PH. Considering the growing importance on strong participation in environmental issues after the 2015 Paris Agreement, testing the weak PH can suggest meaningful economic and political implications for designing "green" regulations to stimulate eco-friendly innovation.

This paper tests the PH using panel data for manufacturing industries between 2011 and 2018 at both industry-level and firm-level. Our measures of innovation activities include the number of patent applications, which captures an innovation output, R&D expenditure, which represents an innovation input. We further look at the patterns of firms' entry and exit as a consequence of innovation outcome. We employ two empirical strategies for our assessment: One is a difference-in-differences (DID) estimation with the matched sample based on propensity score (propensity score matching, PSM). The other is a standard panel regression. In all the multiple empirical tests along with the outcome variables, we find no evidence to be consistent with the weak version of the PH.

Our analysis can largely contribute to the literature in two ways. First, we analyze the regulation impacts at both industry-level and firm-level, considering a majority of the previous literature has focused on testing the PH at only one of the two. Second, only few handful papers on empirical analysis based on the multiple national legislation of managing chemical substances are currently available around the world. Moreover, it is even harder to find relevant studies on the K-REACH and CCA, given the regulations have been recently enforced. In this respect, our research on testing the PH based on the K-REACH and CCA will be the first attempt.

We begin our study with empirical literature review on testing the PH. Section 3 details an overview of the K-REACH and Chemicals Control Act (CCA). Section 4 describes our data, descriptive statistics and regression models. Section 5 provides the empirical results. Section 6 concludes with the policy implications of our findings.

2. Literature review

We distinguish empirical literature on testing the PH into two groups. First set of studies investigates the weak version of the PH that environment regulations drive innovation generally proxied by R&D expenditures (input) and the number of patent applications (output of R&D expense) (Lanoie et al., 2011). The other set of literature tests the strong version that environment regulations lead to higher business performance such as productivity.

An early evidence on the weak version is presented by Lanjouw and Mody (1996). They find a positive impact of increasing interest in environmental protection leads to technological innovation as represented by patenting, in the US, Japan and Germany. This is further developed by Jaffe and Palmer (1997), finding a positive relationship between environmental regulation assessed by pollution abatement costs (PACE) and R&D expense, but no statistically significant association between the regulation and the number of patents in the US manufacturing sectors. However, Brunnermeier and Cohen (2003) find supports that an increase in pollution abatement (per $1 million of the expenditure) costs are positively related with the number of patent applications (an increase of 0.04% in patents). In addition, many other studies find a positive relationship between patenting and environmental regulations (Carrión-Flores & Innes, 2010; de

Vries & Withagen, 2005; Johnstone et al., 2010; Kneller & Manderson, 2012; Lanoie et al., 2011; Lee et al., 2011; Popp, 2003, 2006).

The latter set of papers starts from Jaffe et al (1995) who find a negative effect between environmental regulation and competitiveness measured by productivity. Corroborating the strong PH is settled down by more recent studies. Both Berman and Bui (2001) and Alpay et al (2002) observe positive effects between pollution regulation and productivity growth in the US and Mexico, respectively. Hamamoto (2006) also finds that increases in R&D expenditure caused by an environmental regulatory system have a positive impact on the growth rate of total factor productivity (TFP) in Japanese manufacturing sectors. Leeuwen and Mohnen (2017) show a strong consistency of both versions of the Porter hypothesis with positive relevance of environmental regulations with eco-investment and eco-innovations at Dutch manufacturing firm-level.

However, there are also the relevant studies with mixed or opposite findings. Rexhäuser and Rammer (2014) posit that the strong PH cannot be generalized, but different type of environmental innovation fosters firm's profitability. Lanoie et al (2011) and Rubashkina et al (2015) find evidence to support the weak PH, but no evidence in favor of the strong version. Recently, Wang et al (2019) provide new empirical evidence that environmental regulation enhances productivity growth within a certain level of stringency (lower than 3.08) in OECD countries.

On top of that, there are only very few papers on the K-REACH and CCA. Though the existing papers mostly deal with how much complying costs will increase due to the stringent legislation, not directly with testing on the PH, they can provide some relevant implications in a way that the increased complying costs can discourage a firm's business performance and competitiveness. For the K-REACH regulation, Han (2011) estimates a spillover effect across industries of increased complying costs with a draft of the legislation using input-output analysis. Lee et al (2012) and Kwak and Yoon (2018) analyze both direct and indirect burden costs caused by the chemical regulation. Rhee and Jang (2020) investigate the effects of the regulation on chemical imports using the gravity model and find that it indeed reduces the chemical imports. Cho (2020) also estimates business performance including employment, profitability, and sales for domestic chemical firms (petrochemistry, fine chemistry and rubber and plastic industries) between 2015 and 2017, concluding that the regulation has a significant, negative effect on the performance of fine chemistry industries. For the CCA, there are a few studies that compare the regulation with its previous version of Toxic Chemicals Control Act (TCCA) and political implications for more effective chemical management (Lee, 2013; Chung & Ma, 2016). Given the insufficiency of the previous literature on the chemical legislation, our investigation testing the weak version of the PH using panel data from South Korean manufacturing sectors will contribute to the literature and related policy circles.

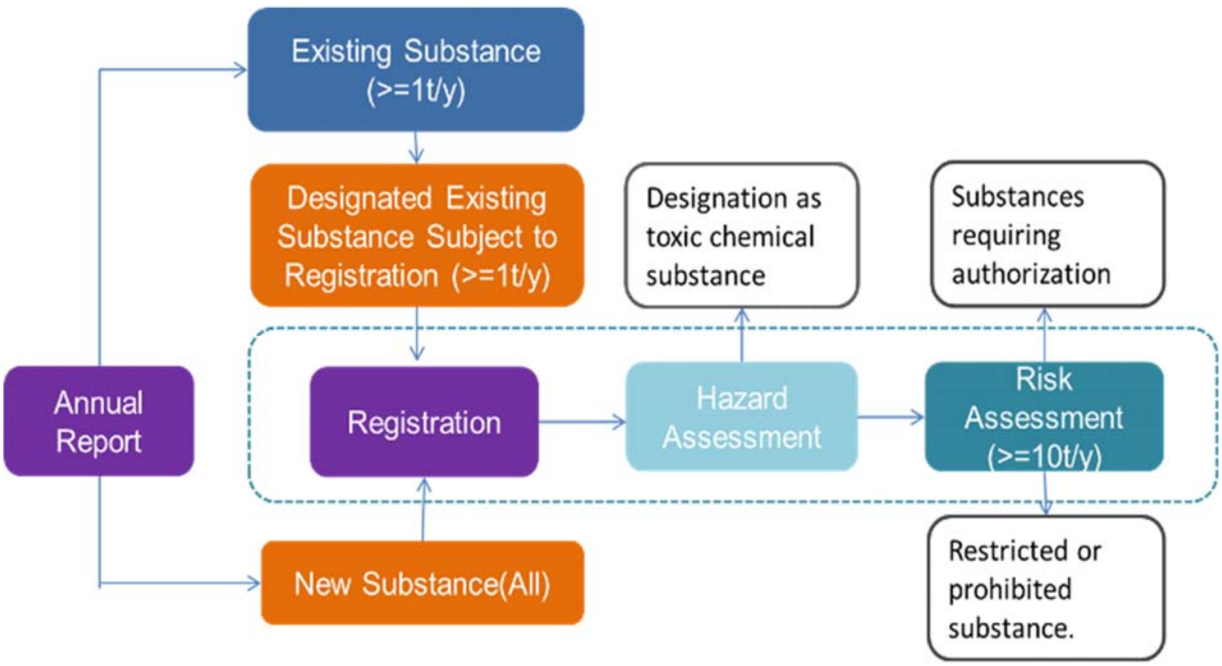
3. Overview of K-REACH and Chemicals Control Act (CCA)

K-REACH (Korea's Act on the Registration and Evaluation, etc. of Chemical Substances) is the Korean version of the EU REACH (Registration, Evaluation, Authorization and Restriction of Chemicals) regulation. It was newly enacted under the Ministry of Environment (MoE) in 2013 and has been enforced since 2015, aimed to protect public health and the environment from potential hazards of chemical exposure. The regulation went through a consequential amendment in 2018, and therefore, the K-REACH is divided into ‘2015 original regulation’ and ‘2018 amendment’.

The K-REACH applies to all business entity, defined as “a person who manufactures, imports, uses, and/or sells chemical substances for the purpose of business”. The regulation classifies chemical substances into 8 types: phase-in substance, non-phase-in substance, phase-in substance subject to registration, toxic substance, substance subject to authorization, restricted substance, prohibited substance and hazardous chemical substance. The main parts of the K-REACH are reporting and registration. First, “phase-in substance” means “a chemical substance domestically distributed for commercial purposes prior to February 2, 1991” or the one if examined before concerning hazards under the former Toxic Chemicals Control Act (TCCA), while “non-phase-in substance” defines “all chemical substances excluding phase-in substances” (Article 2-3). A person who manufactures, imports, or sells more than one ton per year of phase-in substances shall report the usage of the chemical substances, the quantity thereof, etc. to the MoE every year (Article 9). However, if a chemical substance among the phase-in substances is designated to the phase-in substance subject to registration and a person manufactures or imports more than one ton per year, it should be registered. Meanwhile, non-phase-in substances have no standards of usage limit, but all of them should be registered. Once a chemical substance is subject to the registration, it is classified as a hazardous chemical substance, which will go through hazard evaluation and risk assessment afterward (Rhee & Jang, 2020).

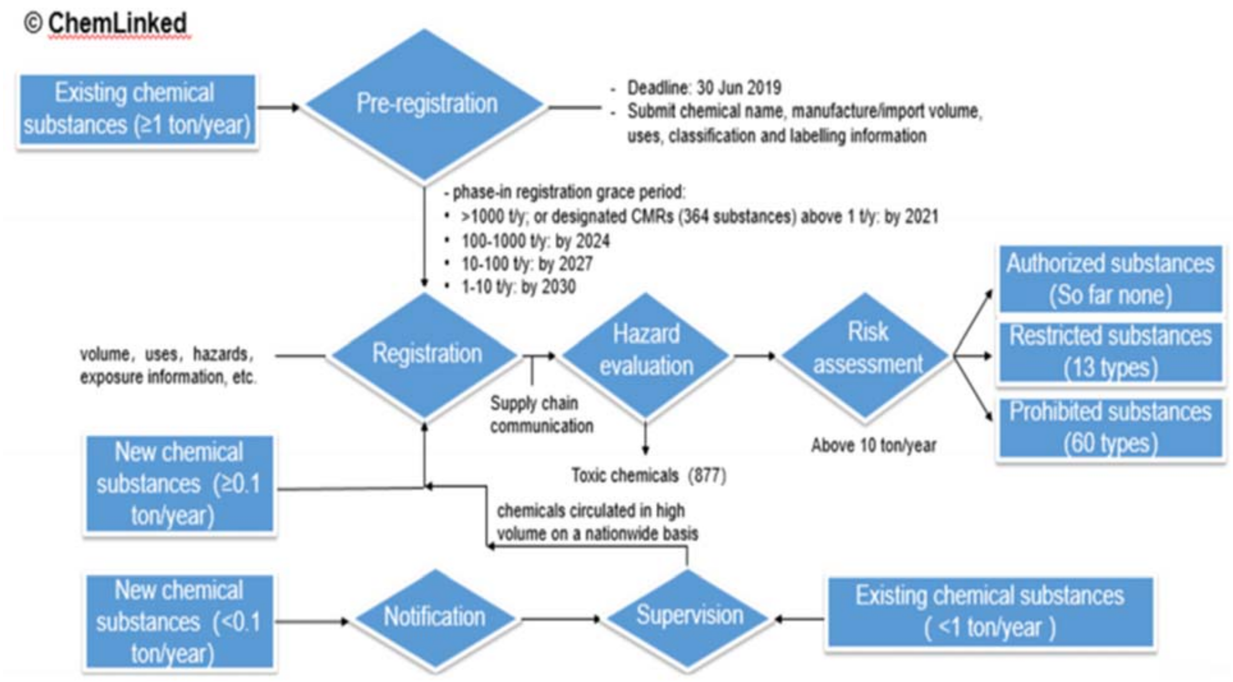
In the revised one, there is a pre-notification stage instead, as the prior reporting was deleted in the procedure. This is important because all phase-in substances should be registered, even if they are not phase-in substances subject to registration. Business entities can get a grace period only if they pre-notify before the registration, and the advantage level of the postponement depends on their amount of distribution. In terms of non-phase-in substances, the amendment set a minimum amount of distribution, so that a person who distributes less than one hundred kilograms per year of the ones do not have to register, but just notify them. A big difference between reporting and registration is a cost. While the reporting in the original legislation only requires brief information on chemical substances without any charge, the registration demands not only detailed data but also registration fees as well as inspection costs, which brings more burdens to the business entities. Given that all the previous reporting is entirely incorporated into the registration, the amendment raises its regulatory stringency compared to the original.

Fig 1. A framework of the original K-REACH



Notes: The image shows the framework of the original K-REACH in 2015. The image is retrieved from Chemsafety website:
http://reachcompliance.blogspot.com/2011/04/korea-toxic-chemicals-control-act-tcca.html

Fig 2. A framework of the amended K-REACH



Notes: The image represents the new framework of the amended K-REACH in 2018, taken from ChemLinked website: https://chemical.chemlinked.com/chempedia/k-reach

Chemicals Control ACT (CCA) is a complete revision of the former Toxic Chemicals Control Act (TCCA) and has been in effect since 2015 along with the K-REACH regulation, to protect the lives and the environment from chemicals "by properly controlling chemical substances and promptly responding to accidents occurred due to chemicals" (*NATIONAL LAW INFORMATION CENTER | LAW SEARCH*, n.d.). It implemented a new system of "evaluation of the impact on the outside of the place of business", which pre-evaluates "the impact of the occurrence of a chemical accident on people, the environment, etc. in the area around the place of business", and "any person who intends to install and operate a hazardous chemical handling facility shall prepare and submit it" to the MoE. For the current status of the two chemical regulations, the Ministry of the Environment provided a 5-year grace period after the K-REACH and CCA of 2015, and therefore the actual efficacy of both regulations has started from 2020.

In this paper, our empirical analysis is based on the two legislation of the original K-REACH and CCA, considering that business entities have newly prepared to comply with both the two strict environmental regulations since 2015.

4. Data and methods

4.1. Data

We exploit both industry-level and firm-level data to assess the Porter hypothesis. On the industry-level, our innovation indicator breaks into innovation input (R&D expenditures) and innovation output (the number of patent applications, entry rate of new firms and exit rate of existing firms). Industrial R&D expenditures in millions of Korean Won, taken from Financial Statement Analysis of the Bank of Korea, represent how much an industry puts efforts as an input for its knowledge and technology production. Inversely, the patent statistics sum up industrial applications as a result of the innovation inputs, taken from Intellectual Property Statistics of the Korean Intellectual Property Office (KIPO). Although either patent or R&D expenditures has been widely used for the innovation indicator in innovation literature (Rubashkina et al, 2015), we also add the firm entry rate measured by the number of new firms out of the total existing firms and the firm exit rate measured by the number of exit firms among the existing firms. The two ratios reflect introducing new products into an industry and subsequent exits of existing products. Both data are available from Business Demography Statistics of the Statistics Korea.

The industry-level data consist of 2-digit or 3-digit industry characteristics depending on the availability of the original data sources where the industry classification follows the 10^{th} revision of Korean Standard Industrial Classification (KSIC). In particular, the patent statistics are constructed using the concordance between IPC (International Patent Classification) and KSIC produced by the KIPO and it provides either 2-digit or 3-digit industry level patent applications. We match all other industry characteristics to this aggregation level.

On the firm-level, data for the innovation indicator (R&D expenses and the number of patents) are taken from Survey of Business Activities of the Statistics Korea.

To identify our treatment group, we measure a chemical intensity indicating which industries highly distribute chemicals and hazardous chemicals, and the data are taken from the National Institute of Chemical Safety (NICS) under the Ministry of Environment (MoE). In our empirical analysis, the chemical intensity is our criterion for the treated industries affected by the two chemical regulations. The NICS provides Statistical Surveys on Chemicals (SSC) of 2014 that include the number of establishments treating chemical substances and hazardous chemical substances at 5-digit industry level, which then converted to our aggregation level.

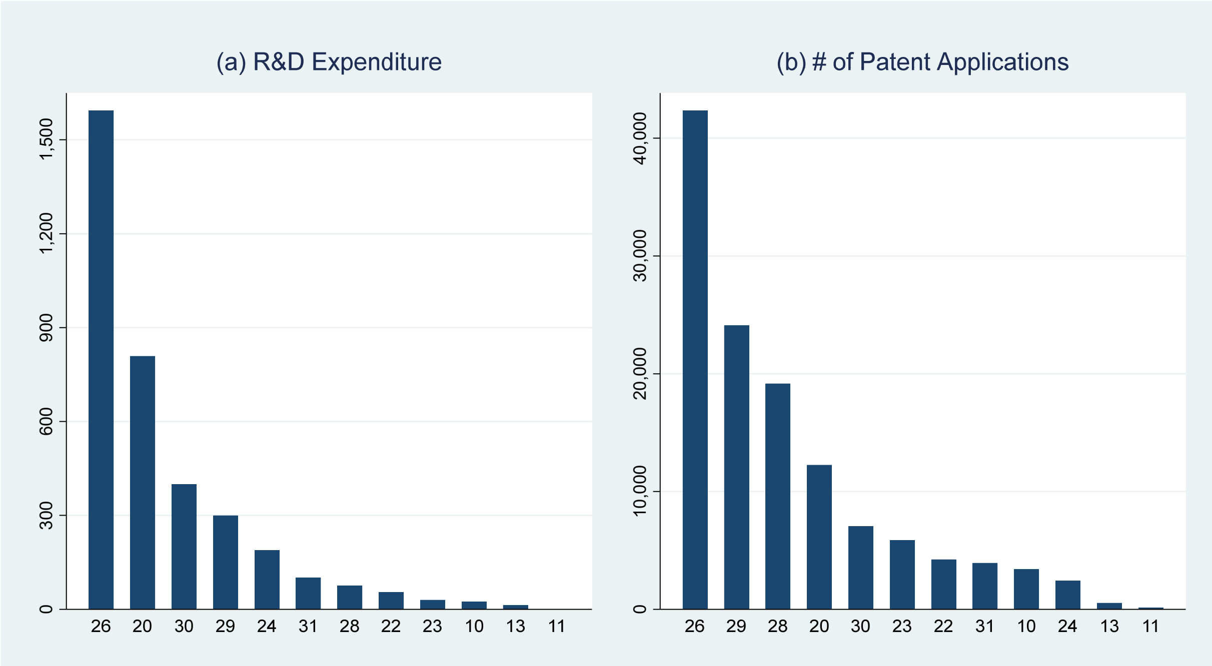
4.2. Descriptive statistics

Before we begin our empirical analysis, we show the innovation pattern and the chemical intensity across industries prior to the implementation of the two regulations in 2015. The innovation pattern can imply which industries tend to highly invest in driving their innovation. We also present the statistical description of the chemical intensity to identify which industries are strongly affected by the two chemical legislative systems.

4.2.1. Industrial innovation

As shown in figure 3, innovation input (R&D expense) and output (the number of successful patent applications) are presented at the 2-digit manufacturing industries between 2011 and 2014. First, on the innovation input, chemical industry (20) is the top two manufacturing industry spending in the investment of R&D, following semiconductors (26). On the innovation output, the chemical industry still remains in the upper ranking, following semiconductor (26), other machinery and equipment (29) and electrical equipment (28). Given the considerable efforts in both types of innovation of the chemical industry and thus important accounts for the country's industrial innovativeness and contribution to the economy, testing the weak version of the PH on the two new regulatory systems can be insightful to identify whether the two stringent regulations have impacts to constrict or boost innovation activities of firms in the chemical sector.

Fig 3. Industrial innovation

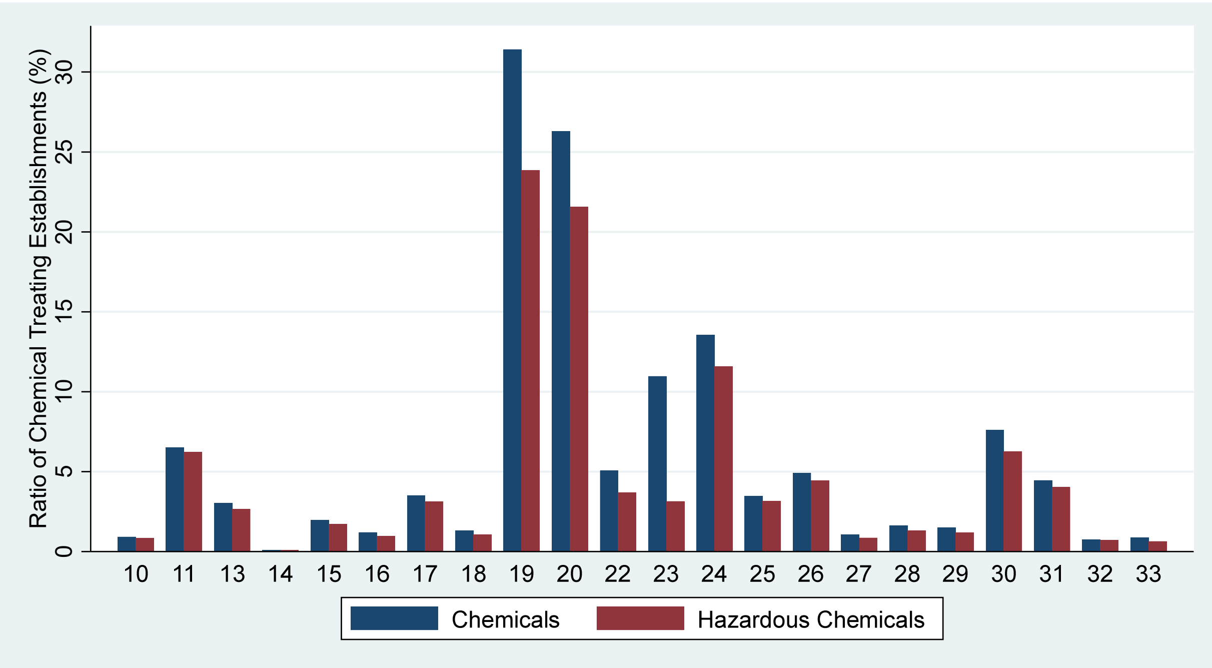


Notes: Industries that have no information on R&D expenditure are omitted. R&D expenditure is in million Won.

4.2.2. Chemical intensity

We measure the chemical intensity dividing the number of the establishments trading in chemical and harmful chemical substances by the entire establishments, respectively. Figure 4 shows industrial difference in the chemical intensity treating chemicals and harmful chemicals of 2014, respectively, at the 2-digit level. Industry 12 and 21 reported the top first and fourth in all the chemical intensity. However, we exclude the two on the grounds that the industry 12 (tobacco products) has only 8 firms among 19 firms distributing both types of chemicals and the industry 21 (pharmaceuticals, medicinal chemical and botanical products) is not applied by the K-REACH (*NATIONAL LAW INFORMATION CENTER | LAW SEARCH*, n.d.). We thus define our treatment group as the top three industries with the ratio of chemical intensity; 19, coke, briquettes and refined petroleum products, 20, chemicals and chemical products; except pharmaceuticals and medicinal chemicals and 24, basic metals.[1] In addition, we further exclude the manufacture of fertilizers, pesticides, germicides and insecticides (denoted by 202 in KSIC 9th and 203 in KSIC 10th) out of the treatment group, as the sub-industry is exempt from the application scope in the K-REACH regulation (Article 2).

Fig 4. Chemical intensity.



[1] The NICS also provides industry-level distribution (including manufacturing, imports, exports and usage) amounts of chemical substances. Before measuring the chemical intensity, we approximately identified the top three industries with the data at the 2-digit level.

4.3. The empirical methods

4.3.1. PSM – DID estimation model

We employ Propensity Score Matching (PSM) - Difference in Differences (DID) method to identify the influence of the two environmental regulations of the K-REACH and the CCA on both industrial-level and firm-level innovation activities before and after 2015 between 2011 and 2018. The DID method is widely used to evaluate a certain impact of policy implementation or external shocks (Fu et al., 2021). In this paper, the DID first captures whether industries are treated (the 2-digit code of 19, 20 and 24) or otherwise. The method then calculates differences for each treated and control group in the impact of the chemical legislation on innovation activities, controlling any other common characteristics such as macroeconomic shocks, government subsidy or supports and other regulations within the matched industries.

Our regression model for the DID estimation is constructed as follows:

$$\ln \mathrm{Y}_{it} = \beta_0 + \beta_1 TREAT_i + \beta_2 POST_t + \beta_3 TREAT_i POST_t + \lambda_i + \delta_t + \varepsilon_{it} \quad (1)$$

where subscript *i* denotes different manufacturing industries; *t* represents different year; *TREAT* is a dummy variable indicating whether the industry is treated or not; *POST* is a dummy variable indicating before and after 2015; the coefficient β_3 for the interaction term, $TREAT_i POST_t$, captures the treatment effect; Y_{it} is an outcome variable of RD, PTT, RNF and REF denoting R&D expenditure, the number of patent applications, rates of new(entry) firms and exit firms, respectively; λ_i is industry fixed effect; δ_t is year fixed effect; ε is the error term.

The key identifying assumption in the DID estimation is that the treated industries would have the same time trends in the outcome variables as the control industries had they not been treated by the environmental regulations. This so-called common trend assumption is not likely to be satisfied if the control industries have fundamentally different characteristics compared to the treated ones. To circumvent this problem, we select proper control industries using the PSM technique before running the DID regression.[2] The propensity score (PS) measuring the probability that industry i will be treated is defined as follows:

$$\mathrm{PS}_i \equiv \mathrm{P}(\mathrm{A} = \mathrm{T}|Z_i) \quad (2)$$

In the equation, $A = \{T, C\}$ indicates both treatment and control group, and Z_i are observable covariates to determine industries for the control group matched with the three treated industries. Rosenbaum & Rubin (1983) show that the PS is sufficient to satisfy the conditional independence where the treated and control industries are well randomized conditional on the observables (Z_i). The observable covariates include (log of) tangible assets, value-added, wages, and the number of patent applications, all divided by the number of employees and averaged over 2011 through 2014. These variables are taken from the Mining and Manufacturing Survey of the Statistics Korea.

We drop some industries (12, 30, 32 and 33) before applying the PSM method, since the industries have only few establishments or distribute very little amounts of chemical substances. We then employ Probit model to estimate equation (2) and select the two nearest control industries based on the propensity scores to that of the treated industries. The matched sample allows a more

[2] The matched sample would also relieve the potential endogeneity problem caused by self-selection, though not completely.

accurate DID estimate by confirming the randomness of the industries and there is no significant difference between each group.

The firm-level analysis follows the same PSM-DID strategy. For the matching, we first assign the treatment group as firms in the top three industry sectors. Then, we use investment in R&D per sales, tangible assets per employees and patent applications per employees taken from the Survey of Business Activity of the Statistics Korea for the observable matching variables using Probit model and the nearest neighboring matching to the first. Firms in the data are subject to companies with over 50 employees. Outcome variables for the DID estimation are RD (R&D expenditures) and PTT (the number of patent applications), taken from the same data source.

4.3.2. Regression model

We also examine changes in the innovation input and output exploiting the differences in industrial chemical intensity, since the higher the industrial chemical intensity is, the bigger cost burdens will be brought for firms to comply the two chemical regulations, which can also affect innovation as a result. Our estimation model for this empirical investigation is as follows:

$$\ln Y_{it} = \alpha + \beta CI_i * POST_t + \gamma \sum lnX_{it} + \lambda_i + \delta_t + \varepsilon_{it} \quad (3)$$

where α is a constant; subscript *i* denotes each manufacturing industry; *t* represents different year; Y_{it} is each outcome variable of innovation (the number of patents, R&D expenditure, entry rate of new firms and exit rate of existing firms), CI_i represents a chemical intensity of an industry i,

$POST_t$ is a dummy variable indicating the treated period after 2015; the coefficient β for the interaction term, $CI_i * POST_t$, captures the marginal effect of the chemical intensity in the post-treatment period on the outcome variables; X_{it} is a vector of control variables; λ_i is industry fixed effect; δ_t is time fixed effect; ε_{it} is the error term. For the key explanatory variable, *CI* (chemical intensity), we use both the chemical intensity of chemical substances and the intensity of harmful chemical substances.

Our control variables of X_{it} include TA (tangible asset), VD (value added), EXP (exports), IMP (imports) and HHI (Herfindahl-Hirschman index). Firstly, TA captures industrial capital intensity by industrial tangible assets per employment, since more innovation activities can be induced by how much capital an industry has. We also include VA for our control variables, not only to control a size of an industry, but also to consider the higher the value-added is owned in an industry, the bigger the innovation can be driven. Above all, competition can be one of the influential triggers to improve or harm innovation (Marshall & Parra, 2019). We thus adopt EXP and IMP for controlling external competition of foreign trades, since international competition of firms can affect to their innovation (Rubashkina et al., 2015). In addition, HHI is an industrial index to proxy market concentration of an industry, which implies that higher market concentration represents lower competition in a product market, whereas lower market concentration indicates the reverse, however, it should not be too high for maintaining competition (Aghion et al., 2005). Based on the economic concept of HHI, we also add its square term for control variables to identify when the market concentration is extremely high. We use our data for control variables (HHI, TA and VD), taken from Mining and Manufacturing Survey of the Statistics Korea. Data for IMP and EXP indicators are adopted from CEPII of the BACI.[3]

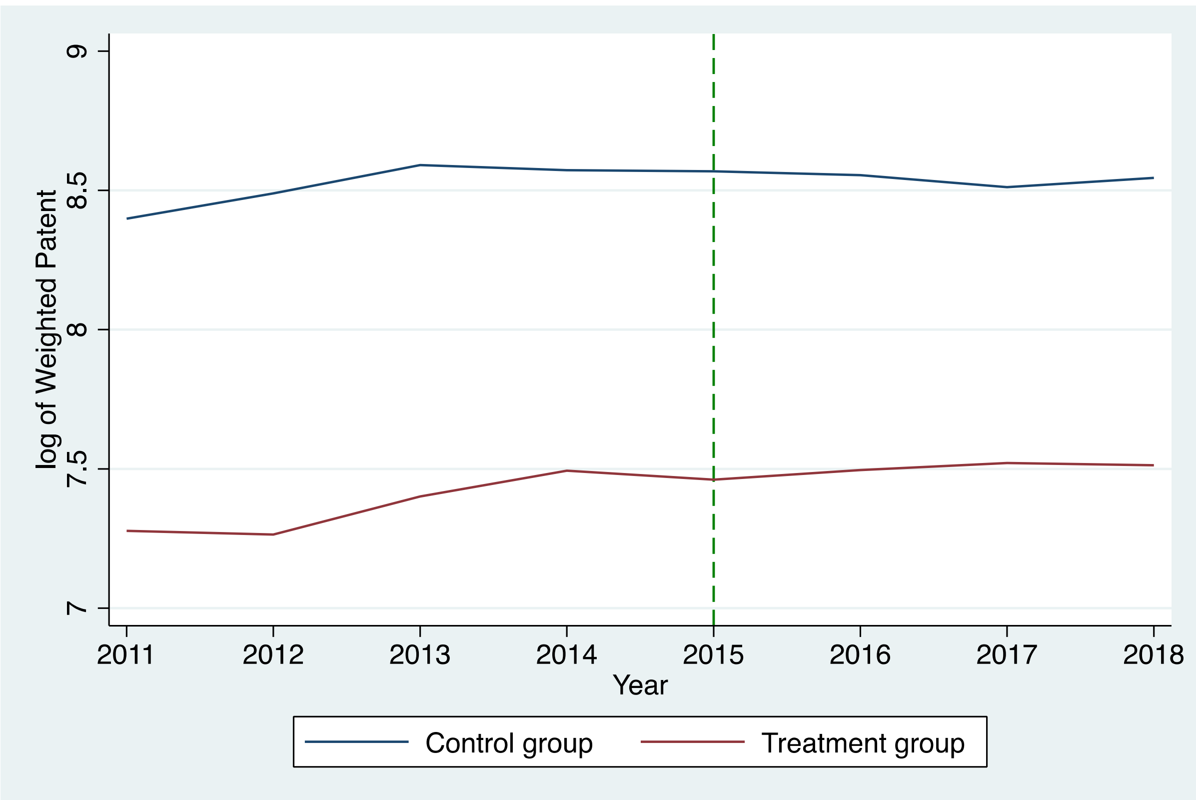
[3] IMP and EXP indicators are taken from CEPII at 6-digit codes of HS 2007, subsequently converted into ISIC 4th revision and finally transferred into KSIC 10th revision.

5. Estimation results

5.1. Parallel trend test

For the accurate DID estimation, the common trend assumption should be preliminarily required. The parallel trend assumption is that the outcome trends of both treatment and control groups should be the same in the pre-treatment period. Figure 5 depicts the trends of the number of patent applications in the treated and control industries, respectively. The green-dashed line is the threshold year of 2015 for the policy implementation. The figure suggests that the assumption is relatively well-satisfied before the treatment outcomes.

Fig 5. Parallel trend test (patents)



5.2. Main estimation results

5.2.1. DID estimation results

Table 1.

Industry-level

	(1)	(2)	(3)	(4)
	Patent	R&D expenditure	Entry rate	Exit rate
$TREAT * YEAR$	.006 (.097)	.126 (.076)	.166** (.057)	.072 (.056)
Adjusted R^2	0.995	0.975	0.613	0.685
No. of observations	112	88	112	112

Notes: The regression is weighted by industrial employment in 2014. The estimation model is with industry fixed effects and year fixed effects. The standard errors are clustered at the industry level in parentheses. ** denotes significance at the 5% level.

Table 1 shows the weighted regression results of the DID estimation. The regression model is weighted by industrial employment in 2014 and estimated with industry fixed effects and year fixed effects. The standard errors are clustered at the industry level in parentheses. Columns of (1), (2), (3) and (4) are the results with the number of patents, R&D expense, the entry rate of new firms and exit rate of existing firms, respectively.

The coefficients of the interaction term ($TREAT*YEAR$) in Columns of (1), (2) and (4) are all positive, but not statistically significant at the 5% level. However, the effects presented by the positive coefficient of Column (3) are significant at the 5% level. This can be interpreted that the two chemical regulations can have positive impacts on innovation by increasing the number of entry firms for the treatment group. However, we further observe the increase in the number of new establishments is caused by a decrease in the entry firms of all control groups during the 2011-2018, not by arising itself. Based on this consideration, we cannot see significant effects of the regulations on the number of patents, R&D expenditure, firm entry rate and exit rate. Thus, we conclude that the results are not consistent with the weak version of the Porter Hypothesis, indicating the two regulations are not positively associated with innovation in the treated manufacturing sectors.

Table 2.

Firm-level		
	(1)	(2)
	Patent	R&D expenditure
$TREAT * YEAR$	-.081	.265
	(.148)	(.177)
Adjusted R^2	0.978	0.962
No. of observations	5,289	1,994

Notes: The regression is weighted by firm-specific employment in 2014. The estimation model is with firm fixed effects and year fixed effects. The standard errors are clustered at the firm level in parentheses.

Table 2 represents the regression results of the DID estimation at the firm level, where it is weighted by firm-level employment in 2014. The estimation model includes firm fixed effects and year fixed effects. The standard errors are clustered at the firm-level in parentheses. Columns of (1) and (2) have the negative and positive coefficients of the interaction term ($TREAT*YEAR$), respectively, with no statistical significance at the 5% level. Thus, a positive relevance between environmental regulations and innovation is not confirmed at both the industry and the firm level based on our empirical results.

5.2.2. Robustness

Table 3.

Industry-level

	Patents		R&D expenditure		Entry rate		Exit rate	
	CH	HCH	CH	HCH	CH	HCH	CH	HCH
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$CI_i * POST_t$	-.014	-.077	-.437	-.372	.480	.565	.083	.132
	(.195)	(.237)	(.590)	(.651)	(.339)	(.394)	(.347)	(.430)
log(TA)	-.270	-.278	1.040	1.068	-.074	-.085	.024	.027
	(.216)	(.214)	(.395)	(.410)	(.322)	(.319)	(.159)	(.156)
log(VD)	.351	.348	.699	.709	.257	.258	.060	.063
	(.116)	(.117)	(.261)	(.264)	(.207)	(.206)	(.115)	(.115)
log(EXP)	-.051	-.049	.064	.053	-.055	-.050	-.083	-.083
	(.036)	(.036)	(.094)	(.093)	(.052)	(.051)	(.059)	(.058)
log(IMP)	.101	.010	-.218	-.206	.028	.023	.172	.172
	(.078)	(.078)	(.218)	(.214)	(.103)	(.104)	(.101)	(.099)
log(HHI)	-52.5	-50.7	458.3	486.0	-87.0	-86.9	-33.3	-34.3
	(44.5)	(44.9)	(772.5)	(786.4)	(39.8)	(40.0)	(18.5)	(18.9)
$\{log(\mathrm{HHI})\}^2$	2.988	2.889	-24.768	-26.285	4.910	4.904	1.899	1.954
	(2.523)	(2.542)	(42.236)	(42.996)	2.264	(2.273)	(1.046)	(1.065)
Adj R^2	0.997	0.997	0.987	0.987	0.826	0.826	0.932	0.932
No. of obs.	272	272	152	152	264	264	264	264

Notes: The regression is weighed by industrial employment in 2014. We use panel data of manufacturing industries between 2011 and 2018, and $POST_t$ is a dummy variable indicating after 2015 with the two policies implementation. The estimation model is industry fixed effects. The standard errors are clustered at the industry level in parentheses.

As shown in table 3, we estimate changes in each innovation indicator of outcome variables (the number of patents, R&D expenditure, firm entry rate and exit rate) depending on chemical intensity (CH and HCH denote the industrial chemical intensity distributing with chemicals and harmful chemicals, respectively). The estimation model (3) is weighed by industrial employment in 2014. The coefficients of the interaction term (*CI*POST*) in Columns (1), (2), (3) and (4) report all negative, but not statistically significant, and the ones in Columns (5), (6), (7) and (8) are all positive, but again with no statistical significance. Based on our regression model (1) and (3), all the econometric results of the impact of the chemical regulations on the innovation at both industry and firm-level find no evidence to support the weak version of the Porter Hypothesis.

5.3. Additional estimation results

The main findings above raise a natural question of whether or not the K-REACH and CCA affect firms' production activities at all. One such activity is import. As the K-REACH requires the imported chemical substances to be reported or registered, firms may circumvent the regulation by reducing direct imports and increasing indirect imports (through intermediaries) or domestic sourcing. To capture these corporate situations where firms may have been newly facing after the regulations, we further estimate whether there have been import changes at the industry and the firm level, using the same regression models (1) and (3), but at this part, the outcome variables are all imports (IMP). Industrial imports are adopted from the CEPII of the BACI, and firm-specific imports in millions of Korean Won taken from the Survey of Business Activities.

In table 4, Column (1) is the weighted regression results of the DID estimation at the industry level where the weight is the industrial employment in 2014. The estimation model includes industry fixed effects and year fixed effects. The standard errors are clustered at the industry level in parentheses. The coefficient of the interaction term (*TREAT*YEAR*) is negative and statistically significant at the 10% level.

Column (2) represents the regression results of the DID estimation at the firm level. The regression is weighted by firm-level employment in 2014 and estimated with firm fixed effects and year fixed effects. The standard errors are clustered at the firm-level in parentheses. At the firm-level, the coefficient of the interaction term (*TREAT*YEAR*) is positive, but with no statistical significance.

Columns (3) and (4) are the regression results showing how the industrial imports change depending on the chemical intensity after the policy implementation. The regression model is weighed by industrial employment in 2014. The coefficients of the interaction term (*CI*POST*) in Columns (3) and (4) are all negative, but not statistically significant.

Table 4.

	Industry-level	Firm-level	Industry-level	
			CH	HCH
	(1)	(2)	(3)	(4)
	log(IMP)	log(IMP)	log(IMP)	log(IMP)
$TREAT * YEAR$	-.267* (.139)	.494 (.365)		
$CI_i * POST_t$			-.158 (.502)	-.104 (.571)
log(TA)			.568 (.265)	.591 (.280)
log(VD)			.520 (.264)	.533 (.273)
log(EXP)			.439 (.033)	.436 (.032)
log(HHI)			60.490 (46.758)	55.837 (45.327)
$\{log(\text{HHI})\}^2$			-3.522 (2.642)	-3.261 (2.563)
Adjusted R^2	0.970	0.909	0.991	0.991
No. of obs.	112	6,536	112	112

Notes: The regressions for columns (1), (3), and (4) are weighted by industrial employment in 2014 and include industry fixed effects and year fixed effects. The regression for column (2) is weighted by firm-level employment in 2014 and estimated with firm fixed effects and year fixed effects. All the standard errors are clustered at the industry and the firm level in parentheses, respectively. * denotes significance at the 10% level.

Overall, imports are all negatively affected by the regulations at the industry level, although the statistical significances are weak. Firm-level estimation result in column (2) shows positive association between the regulations and imports but is not statistically significant. Note that the firm-level results do not reflect small-sized enterprises' actual circumstances because the sample of the Survey of Business Activities is subject to businesses only with 50 or more employees. This can be critical: While firms over a certain size tend to conform to regulations by any means with their sufficient reaction capacity, small- and medium- sized enterprises (SMEs)—particularly with less than 50 employees—are likely to face large administrative costs for regulation compliance. As the industry-level estimation captures businesses of all scales, the statistical consistency of the negative effects on imports can be presumed that the SMEs in the affected industries have reduced their direct imports, rather sought other alternatives of indirect sourcing, to lessen their cost-burdens placed by the chemical regulations.

6. Conclusion

This paper has examined the validity of the (weak version) of the well-known Porter Hypothesis, the nexus between environmental regulation and innovation through the regulatory case of South Korea, the K-REACH and CCA. The analysis is based on panels of manufacturing industries and firms over the period of 2011-2018.

The two chemical regulations have been newly implemented since 2015, but with having a 5-year grace period, which the actual efficacy of the legislation both starts from 2020. What is more, due to the COVID-19 pandemic, the government has temporarily relaxed the regulations to stabilize supply chain of chemical substances until the end of 2021. Under the Porter Hypothesis, we expected firms would prepare to comply with the regulations during the grace period. However, our empirical study finds no econometric evidence on the association between the environmental legislative obligations and innovation activities. Our findings, thus, can be presented in two ways; It may be too early for now to investigate the impact of the regulations on innovative movements given the 5-year stay period, or the regulations may have indeed no positive effect on innovative activities just dampening the competitiveness of domestic firms.

Based on our own interviews, however, the grace period appears to have simply postponed firms, especially small and medium sized enterprises (SMEs), to comply their obligations, in which case the grace period is not useful. If the latter is true, it means that the regulations are not properly designed to foster innovations. Hence, in either case, to achieve the purpose of the two chemical regulations, encouraging companies to make more eco-friendly chemical substances, several supplementary policies should be additionally aligned with the regulations, providing effective incentive to firms so that they put efforts for their own innovation.

Our study contributes to the literature, considering only very few relevant papers have dealt with the chemical regulations. One important feature is that this paper attempts the first to examine the positive effects of the policy implementation based on the relationship with innovation, away from estimating the negative effects, an increase in direct and indirect cost-burdens that previous studies have mostly focused on.

Overall, our study needs to be developed by future research. With strong discussions continued around the country about whether the K-REACH and CCA have an appropriate stringency or whether the regulations could not be actually big burdens to comply, the relationship between the environmental regulation and competitiveness based on the regulatory issues calls for more empirical evidence.

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Appendix.

Appendix 1.
Classification of manufacturing industries
Source: Korea Standard Statistical Classification

#	Sectors
10	Food products
11	Beverages
12	Tobacco products
13	Textiles, except apparel
14	Wearing apparel, clothing accessories and fur articles
15	Leather, luggage and footwear
16	Wood and of products of wood and cork; except furniture
17	Pulp, paper and paper products
18	Printing and reproduction of recorded media
19	Coke, briquettes and refined petroleum products
20	Chemicals and chemical products; except pharmaceuticals and medicinal chemicals
21	Pharmaceuticals, medicinal chemical and botanical products
22	Rubber and plastics products
23	Other non-metallic mineral products
24	Basic metals
25	Fabricated metal products, except machinery and furniture
26	Electronic components, computer; visual, sounding and communication equipment
27	Medical, precision and optical instruments, watches and clocks
28	Electrical equipment
29	Other machinery and equipment
30	Motor vehicles, trailers and semitrailers
31	Other transport equipment
32	Furniture
33	Other manufacturing