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"IMPORT PENETRATION FROM CHINA AND INNOVATION IN OECD COUNTRIES"

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Caterina Giannico

Abstract

In the OECD countries, especially in the US, a huge increase in imports from low-wage countries was registered after China joined the WTO in 2001, and this shock in the manufacturing industrial industry resulted in the beginning of a tough import competition suffered by US and European companies.

In this study, we investigate whether and to what extent, the increased import competition from China has stimulated, or depressed, the inventive activity of advanced countries.

Specifically, we analyze imports from China and IPRs (especially patents) in a panel of fifteen OECD countries between years 1995 and 2019.

Our results show that imports from China and innovation (measured by patent counts) not only follow the same trend but are also linked by a long-run relationship, also robust to control variables, such as the quality of institutions and the R&D expenditure. Such relationship is still significant and strong when dividing the sample of countries into four different macro regions.

Final tests also show a causal relationship between the two variables: in the short run a positive variation in the value of imports from China causes a growth in the number of patents, and the causality is in this direction only, suggesting that the sudden growth in innovation in the early 2000's was due to an exogeneous shock when China entered the WTO and increased its exports towards the OECD countries. In the long run, the causal relationship is mutual, meaning that imports stimulate innovation, but are also attracted and somehow caused by innovation itself.

Keywords: Innovation, Competition, Import, China, OECD

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ARDL: autoregressive distributive lag;

CCE-GM: common correlated effects mean-group;

CD: community design;

CIPS: cross-sectional Im, Pesaran and Shin;

DOLS: dynamic ordinary least squares;

EC: error correction;

ECM: Error Correction Model;

EF: Economic Freedom;

EIS: European Innovation Scoreboard;

EPO: European Patent Office;

EU: European Union;

EUTM: European Union trademark;

GDP: gross domestic product;

GII: Global Innovation Index;

IDI: inward direct investment;

IDV: individualism versus collectivism;

IP: intellectual property;

IPR: intellectual property right;

IV: instrumental variable;

IVR: indulgence versus restraint;

LTO: long term orientation versus short term normative orientation;

M&A: mergers and acquisitions;

MAS: masculinity versus femininity;

MLE: maximum likelihood estimation;

NIC: National Innovative Capacity;

NIS: National Innovation System;

NPV: net present value;

ODI: outward direct investment;

OECD: Organization for Economic Co-operation and Development;

OLS: ordinary least squares;

PDI: power distance index;

PMG: pooled mean-group;

PVECM: panel vector error correction model;

PISA: Program for International Student Assessment;

R&D: research and development;

SII: Summary Innovation Index;

SME: small-medium enterprise;

UAI: uncertainty avoidance index;

UK: United Kingdom;

UN: United Nations;

UNESCO: United Nations Educational, Scientific and Cultural Organization;

US: United States;

USD: United States Dollars;

WGI: Worldwide Governance Indicators;

WIPO: World Intellectual Property Organization;

WTO: World Trade Organization;

1. Introduction

In the OECD context, especially in the US, a huge increase in imports from low-wage countries was registered after year 2001, thanks to a large contribution of imports from China (Chakravorty *et al.*, 2017), the major member of this total volume.

Chinese comparative advantage involves manufacturing industrial goods and China's rapid catch-up in terms of economic growth (also due to a prior large gap during the isolation under Mao (Autor *et al.*, 2016; Brandt *et al.*, 2014; Zhu, 2012)) represented a global supply shock for manufacturing industry and a global demand shock for raw materials (Autor *et al.*, 2016). China joined the WTO in 2001 and previous barriers to exports (expressly forbidden by the WTO) were removed. In this period, there was a shift in Chinese industries from less-productive state-owned companies to private ones raising productivity and output (Autor *et al.*, 2016; Hsieh and Song, 2015).

It all resulted in the beginning of an era of tough import competition suffered by US and European companies, which also caused a differential decline in manufacturing employment and wages. Only Germany partially offset this by increasing exports to Eastern Europe, following the increasing imports from this area (Autor *et al.*, 2016).

The purpose of this study is, however, not investigating the impact of such an increase in import competition from China on labor market dynamics, but analyzing whether, and to what extent, the increased import competition from China has stimulated, or depressed, the inventive activity of advanced countries.

The work is divided into two sections: the first includes the literature review and the main research question; the second presents of the empirical analysis.

After a brief definition of the concept of innovation, the first part of the literature review addresses the most widely used measures of innovation; the second part revises a list of input variables that were used to explain variation in innovation, such as, for instance, trade flows and globalization, institutional factors that characterize the different countries, or cultural differences. The last paragraph of our literature review focuses on the impact of import on innovation: firstly, we discuss the theoretical effects, reporting what researchers found about both factors pushing innovation through import and those inhibiting it; secondly, we report past empirical findings in different countries, periods, methodologies, and firm contexts, concluding that the actual result apparently depends on some main characteristics of the whole context itself.

What emerges from the literature review is that the results of past empirical analyses and the theoretical predictions of possible impacts of imports on innovation remain ambiguous.

On the one hand, importing from other countries raises the competition faced by firms in the domestic area; on the other hand, competition, in turn, could either stimulate companies and push them to innovate, or reduce ex-post innovation rents, lowering profit-cost margins and leaving them with less resources available for investing in R&D.

Other considerations take the knowledge spillover into account and its positive impact on innovation and improvement of products and processes in general, thanks to information and knowledge embodied in manufacturing products.

Managerial personal interests or firm's inertia facing an already-high-quality product, in which other countries are specialized, can also be the mean by which innovation performance is affected, positively or negatively, by a positive variation in imports.

Many geographical contexts have been analyzed, mainly the US, although some analyses were set in Europe or in specific Asian countries.

Our study is specifically set in 15 OECD countries, including 14 European countries and the US, in a period that goes from year 1995 to year 2019, in order to contribute to the literature with an up-to-date analysis of the phenomenon.

After showing introductive graphs and descriptive statistics, we conduct a panel cointegration analysis, using patents as a measure of innovative output and import volumes from China as the main regressor, controlling for variables measuring the quality of national institutions and R&D intensity.

The panel cointegration analysis develops along the following steps. First, we check for the non-stationarity of all our variables, using the Pesaran (2007) unit root test, and finding out that both patents per population and imports from China have a unit root and are non-stationary. Secondly, we perform the Westerlund (2007) cointegration test and we find that the two variables are cointegrated, meaning that they share a common trend and that they are linked by a long-run, non-spurious, relationship.

Then, we estimate the strength and sign of such a relationship using the Dynamic OLS (DOLS), and we find a strong and significant relationship between the stock of patents and the value of imports from China, even when including important control variables (the R&D expenditure, as percentage of the GDP, and the quality of institutions). We find that this relationship is robust across the different areas composing our sample of countries.

Lastly, we check for the actual direction of the causality between the two variables, both in the short and in the long term. Our findings show that the short-run Granger causality is in one direction only: in the short run, variations in imports from China cause variations in innovation, suggesting that China joining the WTO in the early 2000's was an exogeneous shock which caused a growth in the innovative effort of the countries. In the long run, instead, we find that patenting and import competition affect each other.

In the last paragraph, we provide a series of possible explanations for these results, and we present avenues for future research.

2. Literature review and research question

Before starting with the empirical analysis, the theoretical background and the results of previous studies need to be presented.

Thus, the literature review will be divided into three large parts: after a brief definition of the concept of innovation, the first part addresses the most widely used measures of innovation and, in addition to them, other methods that were used to assess this aspect; the second part revises a list of input variables that were used to explain variation in innovation, such as, for instance, trade flows and globalization, institutional factors that characterize the countries included in the samples, or cultural differences. The last paragraph of our literature review focuses on the impact of import on innovation: firstly, we discuss the theoretical effects, reporting what researchers found both about factors pushing innovation through import and about those inhibiting it; secondly, we report past empirical findings in different countries, periods, methodologies, and firm contexts, concluding that the actual result depends on some main characteristics of the organizational and competitive context.

2.1 Previous academic studies

2.1.1 Measures for innovation and variables used in previous academic studies to explain its variation

2.1.1.1 Measures for innovation

Innovation can be defined as "a separate activity through which inventions are carried out in the market for commercial purposes" (Aleknavičiūtė *et al.*, 2016, p. 115) or as "the development of new products, new processes, new sources of supply, the exploitation of new markets and/or new organizational forms" (Aleknavičiūtė *et al.*, 2016, p. 155). A business innovation is defined by OECD/Eurostat (2018) as "a new or improved product or business process (or combination thereof) that differs significantly from the firm's previous products or business processes and that has been introduced on the market or brought into use by the firm"

(p. 68). According to this definition, “the minimum requirement for an innovation is that the product or business process must have one or more characteristics that are significantly different from those contained in the products or business processes previously offered by or used by the firm. These characteristics must be relevant to the firm or to external users” (OECD/Eurostat, 2018, p. 69). The concept of “significant” difference excludes minor changes or improvements from the definition of innovation. However, the boundary between a change that is sufficiently “significant” and one that is not is unavoidably subjective because it depends on each firm’s context, capabilities, and requirements. Such innovation can also be the result of sequential minor improvements, as long as the sum of those improvements results in a significant difference in the final product or business process (OECD/Eurostat, 2018). The Organization for Economic Co-operation and Development also includes in the definition of innovation new marketing methods, new organizational methods in business practices, workplace organization or external relations (Dang, 2017). What is always important to stress is the distinction from the concept of invention: to be considered an innovation, the introduction into the market needs to be involved (Makkonen and van der Have, 2013; Schumpeter, 1934). But just because the usual definitions of innovation are very broad, finding a measure for it is not easy: each measure may not be able to capture all the possible aspects and elements that could represent innovation, and, moreover, methods could be biased towards different directions and affect the results of the different studies, “or the information on which public policy-makers base decision-making” (Makkonen and van der Have, 2013, p. 248).

Here below, we report some of the parameters that were used to assess innovation in past studies.

Table 1: Pros and shortcomings of the main types of measures for innovation.

Innovation measure	**Pros**	**Cons**
R&D expenditure	• Objective quantitative measure; • Easy access.	• Penalizing efficient use of R&D resources; • excluding private inventions by entrepreneurs; • not all efforts result in successful innovations; • excluding several other innovation inputs.

Patent counts	• Being by definition related to innovation, as small quanta of innovation; • ability to exclude small incremental improvement from the actual innovation counts; • relatedness to the increasing importance of intellectual property rights (especially in the high-tech sector); • best choice for accessibility and availability.	• Excluding innovation in services; • not every innovation is patentable; • not every patent has the final goal of innovating; • not measuring the economic value and the quality of each innovation (although such downside is overcomable by weighting patents for citations); • being affected by the size and the sector of the firm.
Composite indexes	• Capturing more relevant aspects of innovation (both inputs and outputs, including R&D expenditure and patent counts).	• Many different indexes lead to many different results and political messages; • complexity in constructing them and accessing data that are needed.
Surveys and questionnaires	• Including both innovation output and divers; • measuring the actual output of innovation.	• No full objectivity; • estimated answers and low response rates; • heterogeneous in technological novelty and economic value.

The most utilized measures to assess level of innovation are R&D expenditure and patent counts, but both of them have their shortcomings.

The main input measure is the R&D expenditure (Acs *et al.*, 2002; Aghion *et al.*, 2018; Donoso, 2016; Krammer, 2009). R&D is defined by the *Oslo Manual 2018* (OECD/Eurostat, 2018) as "creative and systematic work undertaken in order to increase the stock of knowledge and to devise new applications of available knowledge" (p. 87), and, according to the *Frascati Manual 2015* definition (OECD, 2015), R&D activities must meet five criteria: novelty; creativity; addressing an uncertain outcome; systematicity; transferability and/or reproducibility. R&D comprises basic research, applied research, and experimental development. However, this measure suffers from measuring only the budgeted resources allocated towards trying to produce innovative activity (Acs *et al.*, 2002) and it surely penalizes companies that use R&D more efficiently (Aghion *et al.*, 2018). Moreover, it fails "to account for important inventions made by private inventors or entrepreneurs" (Donoso, 2016, p. 2). Past researchers underline the fact that R&D expenditure only measures the allocated resources to innovate, but not all R&D efforts are necessarily followed by successful, or commercialized innovation outputs (Acs *et al.*, 2002; Gu and Tang, 2004; Nelson, 2009; Makkonen and van der Have, 2013). In fact, the definition of innovation itself does not require an innovation to be a commercial, financial, or strategic success at the time of measurement (OECD/Eurostat, 2018). For example, technological process can be cumulative and last long periods and companies could perform their R&D strategically, just to keep a technology area occupied for some time, rising costs of catching up and lowering competition pressure just by creating a barrier to entry to deter new potential rivals (Lieberman, 1989; Makkonen and van der Have, 2013; Perez and Soete, 1988), or a product innovation can simply fail commercially or a business process innovation may just require more time to meet its objectives (OECD/Eurostat, 2018). Also, R&D efforts are just one of the several inputs needed in order to innovate, such as production or marketing (Kleinknecht *et al.*, 2002; Makkonen and van der Have, 2013; Ratanawaraha and Polenske, 2007). Indeed, a definition of innovation activities is provided by OECD/Eurostat (2018) and indicates them as "all developmental, financial and commercial activities undertaken by a firm that are intended to result in an innovation for the firm" (p. 68). There are actually eight types of activities, listed by OECD/Eurostat (2018), that a firm can undertake to pursue innovation: research and experimental development (R&D) activities; engineering, design, and other creative work activities; marketing and brand equity activities; IP-related activities; employee training activities; software development and database activities; activities related to the acquisition or lease of tangible assets; innovation management activities. Lastly, several authors claim that "certain sectors as well as micro firms and small firms tend to be underrepresented in R&D data" (Makkonen and van der Have, 2013, p. 250).

However, R&D expenditure is one of the most used measures for innovation in research and it's still seen as a valid indicator (Acs *et al.*, 2002; Makkonen and van der Have, 2013): it's still an objective quantitative measure, it's easier to collect, comparing it to other kinds of data, and it's not affected by the downsides of patent counts or other methods to assess and measure innovation.

Patent counts are the main output measure for innovation (Aghion, *et al.*, 2018; Krammer, 2009; Makkonen and van der Have, 2013), they are free from the limitations of R&D expenditure, they "are the most commonly used quantitative measure […], because, by definition, they are related to innovation" (Taylor and Wilson, 2012, p. 238) and they are presented either as an absolute number or per million inhabitants and weighted for their citation rate (Andrijauskiené and Dumčiuviené, 2019; Boly *et al.*, 2014; Furman *et al.*, 2002; Trajtenberg, 1990). Each patent represents an individual "quantum" of invention that has passed the muster of trained specialists and won the support of investors and researchers who dedicate their time, effort, and resources to research and to acquiring legal protection. The use of patents to measure innovative activity was pioneered in the 1960s by Scherer (1965) and Schmookler (1966) who used patent statistics to investigate the demand-side determinants of innovation (Taylor and Wilson, 2012). Nevertheless, they have more than one critic point as well. First, they measure innovation in the field of manufacturing, but they may not be able to capture those innovations that involve services, so that some innovations escape measurement. Consequently, this tool, used to capture innovation in general, creates a gap between the actual and the measured innovation, and the more the economies are service based, the wider this gap is (Andrijauskiené and Dumčiuviené, 2019; Camacho and Rodríguez, 2005; De Liso and Vergori, 2017; Hipp and Grupp, 2005; Makkonen and van der Have, 2013). Another downside is the fact that "not every innovation is patentable and not every patent is used to create an innovation. In practice, large corporations often file many patents but are able to use only a certain percentage of them to create products" (Andrijauskiené and Dumčiuviené, 2019, p. 573). Moreover, patent counts do not actually measure the economic value of such innovations, which may differ, and not always slightly, among them (Acs *et al.*, 2002; Makkonen and van der Have, 2013), together with the quality of the innovation that iss patented and its overall impact, so that minor innovations are mixed and considered just like the revolutionary ones (Taylor and Wilson, 2012), even though the tiniest innovations are not patentable at all. Thus, the positive side of this measure is being able to exclude modest adaptations from the innovation counts (Fagerberg and Srholec, 2008; Hall *et al.*, 2005; Makkonen and van der Have, 2013). Also, the propensity to patent is affected by the size of the firms, for example due to economies of scale (Acs *et al.* 1992; Arundel and Kabla, 1998; Makkonen and van der Have, 2013), and this "implies that the spatial distribution of large and small firms may distort the measured regional innovativeness when approximated through patents" (Makkonen and van der Have, 2013, p. 250). Another drawback of patents as an innovation measure is the fact that, in addition to firm and sector characteristics, they are also affected by the innovations themselves: a firm could decide whether to patent an innovation or not depending on some characteristics, such as the degree of novelty and complexity (Mäkinen, 2007; Makkonen and van der Have, 2013), and this choice is obviously not fully objective.

Despite all the downsides, patents remain "a good way to track flows of knowledge across firms, sectors and countries", and moreover, during the last decades the number of innovations patented has very much increased, together with the "increasing importance of intellectual property in today's knowledge-based economy" (Krammer, 2009, p. 846). Like any other proxy, they present disadvantages, but, according to Krammer (2009) and Griliches (1990), they are still the best available source for the assessment of technological change and innovation, since nothing else is comparable in terms of quantity of available data, accessibility, and potential industrial organizational and technological details.

A way to overcome all the possible downsides of the two previously mentioned measures is the assessment of innovational activity by constructing indexes based on more than one indicator (indeed, they are also known as composite or multidimensional indexes) (Donoso, 2016), so to capture some aspects of innovation that otherwise statistics would fail to take into consideration. Many indexes have been used in past studies, taking both input and output factors into account simultaneously (Booysen, 2002; Carayannis and Provance, 2008; Makkonen and van der Have, 2013). They "have been constructed from a variety of measures, broadly divided between measures of inventive or innovative activity, and measures that capture the preconditions, or the capacity for innovative activity" (Makkonen and van der Have, 2013, p. 251). Anyway, R&D expenditure and patent counts are always included among the main indicators of any index (Makkonen and van der Have, 2013).

For instance, Hollanders and Arundel (2007) make use of the Summary Innovation Index (SII), which was developed by the European Innovation Scoreboard (EIS), in order to measure the innovation performance of the EU Member States. The SII is a composite index which measures the innovation performance of the countries by taking the average of 25 indicators which represent 25 different aspects of the innovation process and are split into five innovation dimensions: innovation drivers, knowledge creation (measuring R&D investments), innovation and entrepreneurship (of the firm), applications, and intellectual property (a possible output of the innovation process, such as patents).

Cox and Khan (2017) use an even richer index, which utilizes 80 indicators of national innovation: the Global Innovation Index (GII). It consists of two sub-indexes, measuring innovation-related inputs and innovation-related outputs. Innovation-related inputs are: institutions (political, regulatory, and business environment); human capital and research (education, research and development); infrastructure (information and communication technologies, energy supply, and general infrastructure); market and business sophistication (credit, investment, trade, competition); worker knowledge, innovation linkages, knowledge absorption. Innovation-related outputs are scientific outputs and creative outputs. The GII reports information from the World Bank, UNESCO, and other sources and has been analyzed and validated by the European Commission Joint Research Center.

Other examples of composite indexes are the National Innovation Capability Index developed by Porter and Stern (Cox and Khan, 2017) or the International Innovation Index, developed by a consortium of US businesses led by the Boston Consulting Group (Steel *et al.*, 2012).

However, some concerns were raised in relation to the use of composite indexes on a regional level: "even well-accepted methods to construct indexes can lead to drastically different results", therefore, they "can potentially send non-robust policy messages […], increase the quantity of required data. Thus, although indexes might appear at first glance to be a sophisticated way to measure innovation, there are also limitations to them". (Makkonen and van der Have, 2013, p. 251).

Some researchers chose to measure innovation by its actual output (Aleknavičiūtė *et al.*, 2016) by means of questionnaires and surveys inquiring firm representatives to indicate the number of newly introduced or significantly improved products/services/processes or their share of sales during a fixed period of time (Barbosa and Faria, 2011; Makkonen and van der Have, 2013). Surveys usually include key company data, such as employment, sales value, ownership type, industrial sector, and date of incorporation, but they can also include questions about the size of the company, the productivity, the skills, the size of the city and of the region where the plant is located, the impact of the innovation on the business, the sources of information used, the process of innovation, and questions related to other variables of the model, which, in our case, would be, for example, question about the trade flows (Barbosa and Faria, 2011; Gonchar and Kuznetsov, 2018).

Nevertheless, in the literature there are a number of shortcomings related to firm-level innovation data collected with questionnaires, concerning more than one aspect: as we previously briefly mentioned, they are not completely objective, as the respondent has their own idea about what an innovation is and their answer is based on that hypothesis (Ratanawaraha and Polenske, 2007; Makkonen and van der Have, 2013). Results could diverge depending on the respondent's perspective, beliefs, and context (Galindo-Rueda and Van Cruysen, 2016; OECD/Eurostat, 2018). Indeed, "some forms of novelty, such as *disruptive* or *radical* innovations, and some types of economic impacts are difficult to identify within the limited observation period recommended for innovation surveys" (OECD/Eurostat, 2018, p. 77). Secondly, surveys sometimes suffer from estimated answers and low response rates, as the firms themselves are supposed to provide the data but may or may not be willing or able to do that: this problem may make regional comparisons very difficult (Kleinknecht *et al.*, 2002; Makkonen and van der Have, 2013). Thirdly, as well as other methods to assess innovation, they can lead to extremely heterogeneous response on technological novelty and economic value of reported innovations (Makkonen and van der Have, 2013; Rothwell and Gardiner, 1988).

Despite some downsides, surveys are still a pretty widely used method to measure innovation in the research, and do not suffer from many of the limits of the previously mentioned proxies.

2.1.1.2 Variables used in previous academic studies to explain variation in innovation

Variation in innovation performance of countries may be explained by many different contextual factors, year-specific events and firm and sector-specific characteristics. However, we will cite just some of them, since they are the most used in past empirical analyses.

A variable that was often used in past studies to explain innovation was based on institutions. A single definition of the term "institution" is difficult to find, as it can represent different aspects of economic, legal, political, and social activity in a geographical context (Barbosa and Faria, 2011). In the seminal contribution, institutions were defined as the rules of the games in a society (Barbosa and Faria, 2011; North, 1990). Many other authors followed this type of perspective. Hwang and Powell (2005) define them as "the creation of formal laws, that defines the playing field, enabling the efforts of certain groups and retarding the efforts of others" (Barbosa and Faria, 2011, p. 1158). Barbosa and Faria (2011, p. 1158) focus "on administrative and economic practices and policies aimed at regulating the product, labor, and capital markets, as well the intellectual property systems": these aspects do not reflect all institutional dimensions, but they fit the authors' (and our) innovation perspective, as "they include some of the most important structures and forces that shape and maintain the institutional environment affecting innovation activities" (Barbosa and Faria, 2011, p. 1158).

The neo-Schumpeterian theory of innovation stresses the role of institutions in fostering innovation activities (Khedhaouria and Thurik, 2017; Nelson and Winter, 1982) and relations between government agencies and private firms and technology policies are examples in which institutions can influence innovation (Khedhaouria and Thurik, 2017). Institutions make regulations and the term "regulation" refers to the implementation of rules by public authorities and governmental bodies in order to influence market activity and the behavior of private actors in the economy and in the society (OECD, 1997). Several types of regulations can affect the innovation activities of firms, industries, and economies (Blind, 2013), including regulations on product markets, trade and tariffs, financial affairs, IPRs, employment and labor market (OECD/Eurostat, 2018). Indeed, the *Oslo Manual 2018* (OECD/Eurostat, 2018) stresses the importance, when dealing with innovation analyses, of assessing business views on the macroeconomic policy governmental contexts.

Firstly, institutional role regards product market regulation, implemented through anti-trust policies. In fact, "the primary task of government intervention in innovation diffusion would be to facilitate the dynamic functioning of markets (Caiazza, 2015, p. 1407; OECD, 2013) […] through a vigorous competition policy, smooth macroeconomic policy or regulatory reform" (Caiazza, 2015, p. 1407; OECD, 2011) and, according to the public interest theory, regulation corrects market failures, thus protecting public interest. On the other hand, public choice theory sees regulation as an advantage for large incumbents (Barbosa and Faria, 2011; Stigler, 1971), giving them a high market power and impeding new entrants to invest in innovation. Summarizing, anti-trust policies have an impact on competition and competition may, in turn, have different impacts on innovation, according to different authors (Barbosa and Faria, 2011), such as Schumpeter (1942), Arrow (1962), or Aghion *et al.* (2005).

Beside by affecting competition, anti-trust laws can (negatively) impact innovation by leading to a smaller average firm size (Barbosa and Faria, 2011; Kumar *et al.*, 1999), which is usually positive correlated with innovation. Another important aspect to take into account is entry regulation, including start-up costs. If they are high, they can represent a barrier to entry, hindering the introduction of innovation by entrepreneurs who would like to start a new business (Barbosa and Faria, 2011).

Another aspect involved by institutions is represented by labor market regulation, naming the "legislation regulating hiring and firing practices, wages, and unemployment insurance" (Barbosa and Faria, 2011, p. 1159). On this topic, opposite results were anticipated by the literature and showed by empirical analyses. On the one hand, a rigid regulation of hiring and firing may increase the bargaining power of unions, making it more difficult for a company to invest in R&D and to adjust wages after implementing an innovation. Dismissal laws can also make it more difficult to adapt to new technologies that require the reallocation of staff or downsizing (Barbosa and Faria, 2011). On the other hand, unions or stringent dismissal laws may incentive employers to train employees and invest in their productivity, motivation and engagement (Barbosa and Faria, 2011; Acharya *et al.*, 2010). Anyway, it was found "that the impact of employment protection policies on innovation depends on the state of industrial relations […] and on the industry's level of technology. Overall, […] results suggest that strict employment protection policies are likely to negatively affect R&D intensity" (Barbosa and Faria, 2011, p. 1159).

Institutions also regulate capital markets and financial development can affect innovation as well. It was found to foster entry of firms and lead to a more competitive environment (Barbosa and Faria, 2011; Guiso *et al.*, 2004; Kumar *et al.*, 1999; Macchiavello, 2006; Rajan and Zingales, 1998). Empirical analyses also show that financial constraints "prevent new firms from attaining their optimal initial size" (Barbosa and Faria, 2011, p. 1159) and credit availability is fundamental for firm growth and survival (Barbosa and Faria, 2011; Clementi and Hopenhayn, 2006; Guiso *et al.*, 2004). It was argued that firms that achieve their optimal size are expected to be facilitated in engaging in innovation (Barbosa and Faria, 2011). Empirical research shows a positive impact of credit availability on the foundation of technology-based firms and on firms' innovation effort (Audrestch and Elston, 2006; Barbosa and Faria, 2011; Bottazzi and Da-Rin, 2002; Cassar, 2004). Evidence also shows "that venture capital favors the entry of new firms and/or small firms, particularly technology-based start-ups. So, we can expect that financial development will have a positive and larger effect in industries with high innovation intensity where small firms can enter and compete" (Barbosa and Faria, 2011, p. 1160).

Lastly, but maybe most importantly for our analysis, institutions affect innovation through regulations on intellectual property rights (henceforth, IPRs), such as patents. IPRs have the aim of incentivizing to engage in research and disclose information about the results: they incentivize ex ante innovation by providing ex post monopoly rents (Aghion and Howitt, 1992; Barbosa and Faria, 2011; Economides *et al.*, 2007; Eicher and García-Peñalosa, 2008; Romer, 1990), limited both in time and scope (Varsakelis, 2006), since they allow temporary appropriation of technological innovations and reduce uncertainty about possible appropriation by third parties (Edquist and Johnson, 1997; Varsakelis, 2006). Moreover, secure property rights facilitate foreign direct investment (henceforth, FDI) and trade, thus helping international technology transfer and diffusion (Barbosa and Faria, 2011; Coe *et al.*, 2008; Helpman, 1993), and also, “IPRs may facilitate start-ups in some circumstances by giving an inventor the time to get established in the industry” (Barbosa and Faria, 2011, p. 1160).

Empirical evidence observes that strengthening a patent system results in an increase in patenting and in the use of patents as part of the strategy of many firms (Barbosa and Faria, 2011; Hall, 2007).

More generically, national innovation systems theory underlines the importance of institutions and organizations for the production of new knowledge (Varsakelis, 2006), as one of the main determinants for technological development (Edquist, 1997; Lundvall *et al.*, 2002; Varsakelis, 2006). Economic and social institutions explain the cross-country variation of innovation activity (Varsakelis, 2006). In any case, Varsakelis (2006, p. 1085) also claims that “the ability of a country to implement a law depends on the quality of government agencies such as the judiciary system as well as the political stability”, since the efficiency of the judiciary system, political stability, accountability of governmental actions, and low corruption should be positively related to patents rights and consequently to innovation, as well as corruption and bureaucratic inefficiency are showed to be negatively associated with investment and consequently with innovation (Varsakelis, 2006; Mauro, 1995). Indeed, systemic imperfections, such as capabilities, institutions, networks and framework failures can hinder the realization of synergies between actors involved in the innovation diffusion process (Arnold, 2004; Caiazza, 2015; OECD, 2009). According to Caiazza (2015), institutional barriers are in general legal, economic, technical, and cultural obstacles related to the context in which the diffusion process is realized. Such barriers could consist of “weaknesses in legal (regulatory impediments, uncertainty in intellectual property rights, etc.) and economic (financial mechanisms, fiscal structure, etc.) frameworks” (Caiazza, 2015, p. 1409). Reforms of intellectual property protection, environmental regulation, and labor markets affect the regulatory framework that can facilitate (for example, through tax incentives or favorable depreciation schedules) or hinder innovation in a range of policy areas from the general business environment to international trade, international investment, financial markets, labor markets and education (Caiazza, 2015).

As long as many researchers use institutional quality as a variable to explain variation in innovation, they can find available several of them, designed both by the World Bank and by the OECD to measure the institutional and regulatory environments of countries (Barbosa and Faria, 2011).

As well as some other authors (Celikel-Esser, 2007; Hollanders and Arundel, 2006; Hollanders and Arundel, 2007), we chose the Worldwide Governance Indicators (henceforth, WGI) elaborated by the World Bank. The World Bank itself defines governance as "the traditions and institutions by which authority in a country is exercised. This includes the process by which governments are selected, monitored and replaced; the capacity of the government to effectively formulate and implement sound policies; and the respect of citizens and the state for the institutions that govern economic and social interactions among them". The WGI report six dimensions of governance. *Voice and accountability* "captures perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media"; *political stability and absence of violence/terrorism* "measures perceptions of the likelihood of political instability and/or politically-motivated violence, including terrorism"; *government effectiveness* "captures perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies"; *regulatory quality* "captures perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development"; *rule of law* "captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence"; *control of corruption* captures perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests"[1].

Zhu and Zhu (2017) use the overall effectiveness of a country's regulatory system as explanatory variable for innovation variation in US companies, measuring such effectiveness with the index of economic freedom. A country's economic freedom captures the fundamentals of its institutional framework, and its four major categories are rule of law, limited government, regulatory efficiency, and open markets. The index of economic freedom (EF) "measures cross-national differences in a country's judicial system and its economic prosperity" (Zhu and Zhu, 2017, p. 54) and is built weighting ten components: property rights, freedom from corruption, fiscal freedom, government spending, business freedom, labor freedom, monetary freedom, trade freedom, investment freedom, and financial freedom. Property rights measure the ability of rights to protect private property and its law enforcement; freedom from corruption is "the perceived level of corruption in a county through legal, judicial, or administrative levels"; "fiscal freedom is […] the lack of burdensome taxation"; freedom-from-government spending

[1] Worldwide Governance Indicators (WGI): https://info.worldbank.org/governance/wgi/Home/Documents

measures how effectively the government uses the resources collected from taxes; business freedom is "the costs that firms must undertake if they open, operate, or close a business, as well as when they obtain a license" and "indicates the efficiency of a country's rules and regulations"; labor freedom is "the freedom of participants in the economy to choose where and how their labor is allocated in the economy without the interference of government mandates on price controls (i.e., minimum wages) in the labor market"; monetary freedom measures the ability of the government to stabilize and maintain the relative price of goods and services in the markets; trade freedom measures the degree to which firms within the economy are allowed to freely trade with partners and free from government intervention in the form of tariffs or nontariff barriers; investment freedom is similar, but "it is specifically targeted at the ability of both individuals and companies to invest in foreign or domestic interests"; financial freedom measures the "independence of the financial markets and banking efficiency" (Zhu and Zhu, 2017, pp. 52-53).

Taylor (2009) focuses on institutions more as democracy, property rights, and markets for trading them. Such aspects are often invoked by economists like Arrow (1962), Mokyr (1990), Nelson (1993), Acemoglu *et al.* (2005) and Rodrik (2007). For these three elements, Taylor uses three different indexes, including the index of economic freedom (EF) used by Zhu and Zhu (2017).

Another variable that was used by some researchers to explain variation in innovation is national culture. Hofstede *et al.* (2010) defines culture as the "software of the mind" or as a "collective programming of the mind", meaning that it's a shared system of meanings through which reality is communicated and deciphered. It guides our perceptions and behavior. If we talk about different countries, the cultural groups we refer to is obviously the national one, meaning that we can distinguish the main patterns of national culture, seeing in what they are mostly different or similar.

Being surrounded by their national context and being supposed to be composed of many people of the same country, companies are expected to be affected by national culture of where they are located. That's why Cox and Khan (2017) studied how national innovation could be affected by national culture basing such variable on Hofstede's six cultural dimensions, which allow to compare different cultures by using the scores of the six dimensions, which are: *power distance index (PDI)*, *individualism versus collectivism (IDV)*, *masculinity versus femininity (MAS)*, *uncertainty avoidance index (UAI)*, *long term orientation versus short term normative orientation (LTO)*, *indulgence versus restraint (IVR)*[2].

[2] Hofstede Insights: https://www.hofstede-insights.com/models/national-culture/

Nevertheless, this explanatory variable is not free from limits. First, national culture can be about the *majority* of people belonging to a nationality, not about all of them; moreover, employees' nationality and culture may not coincide with nationality and national culture of the country where their company is located. In addition, as Cox and Khan themselves mention, "there may be clusters of countries with similar cultural tendencies" (Cox and Khan, 2017, p. 98) but very different in terms of other more significant variables for the explanation of variation in innovation. Moreover, other variables that can be used are quantitative per se, while this one is originally qualitative, thus the analysis may have more subjective bases.

The starting point of the input variable used by Steel *et al.* (2012) is qualitative as well: they assess the relationship between the Big Five personality factors at national level and national innovation performance.

Studies show that the Big-Five structure manifested itself around the world (Rolland, 2002; Steel *et al.*, 2012), thus a valid comparison between nations and can be used to understand national differences in personality of the citizens. The Big Five model by McCrae and Costa includes five personality traits, that lay in individuals in different degrees: *neuroticism*, *extraversion*, *openness to experience*, *agreeableness*, *conscientiousness*. Companies are made of people, who are, ultimately, the initiators and implementors of innovations, so it is reasonable to expect that personality at a national level affects innovation in firms of that nation. Anyway, this approach has also some critics: the first one regards the same aspect limiting the cultural approach we mentioned before, and it is correlated with the subjective nature of the measure of the input variable and with the match of an originally qualitative variable with a quantitative (dependent) one. The second aspect was brought up by other researchers and cited by Steel *et al.* themselves. It has been brought up that five-factor models do not perform well as predictors of cross-national differences in behaviors purportedly related to those factors (Heine *et al.*, 2008; Steel *et al.*, 2012).

As an alternative for explaining variation in innovation, Aleknavičiūtė *et al.*, (2016) focus their analysis on the effect of human capital level on innovative performance. A lot of innovation research emphasizes that innovations are linked to new knowledge creation (Aleknavičiūtė *et al.*, 2016; Iturrioz *et al.*, 2015; Lyles, 2014; Užienė, 2015; Vick *et al.*, 2015; Wang, 2015) that can be examined through the concept of human capital, which is, in turn, structural part of the intellectual capital. Human capital is defined by OECD (as cited by Aleknavičiūtė *et al.*, 2016: OECD, 1998) as "the knowledge, skills, competences and other attributes embodied in individuals that are relevant to economic activity" and in general is associated to knowledge accumulated with education and training (Aleknavičiūtė *et al.*, 2016). In a company, "the main purpose of human capital is to create innovations: to generate new ideas, to create new products, services, or goods, to improve existing products, services, or goods, to establish new business processes and so on" (Aleknavičiūtė *et al.*, 2016, p. 116). In their study, they use the contribution of several authors (Barro, 1996; Barro and Lee, 2011; Benhabib and Spiegel, 1994; as cited by Aleknavičiūtė *et al.* (2016): INSEAD eLab, 2009; Krueger and Lindahl, 2001; Lucas, 1988; Meschi and Scervini, 2014; Morrisson and Murtin, 2013; Rebelo, 1991; Welsum and Lanvin, 2012) and of different surveys (PISA survey, Information and Communication Technologies surveys, and European Social Survey) in order to build their measurement model for human capital (Aleknavičiūtė *et al.*, 2016).

However, the model for the assessment of human capital does not include one important element constituting human capital itself, that is the motivation of employees to engage and contribute to the company by being part of initiators of innovations.

Anyway, in this study, we chose to be more focused on macroeconomic variables concerning the trade flows. Much literature is focused on the impact of imports from China or from low-wage countries in general on innovation in different national and organizational context (Autor *et al.*, 2016; Autor *et al.*, 2020; Bloom *et al.*, 2016; Chakravorty *et al.*, 2017; Dang, 2017; Hombert and Matray, 2017; Iacovone *et al.*, 2011; Shu and Steinwender, 2019; Vancauteren *et al.*, 2019; Yamashita and Yamauchi, 2020), although none of these specific studies is focused on OECD countries as a geographical target.

Nevertheless, some other research analyzes other or more general aspects of international trade.

Aghion *et al.* (2018) investigate the impact of exports to China on French the innovation performance (proxied with patent counts) of private domestic profit-maximizing manufacturing firms. Two contrasting effects were found. The first one, the direct market size effect, has a positive impact on innovation: by exporting goods, firms face an increasing demand for their products, therefore profits will increase as well, thus a larger amount of resources will be available for investment, such as, for example, innovation. The second one, the competition effect, has a negative impact on innovation: when entering new geographical markets selling the same goods, domestic companies have to face the competition of the incumbent, seeing their overall market share decrease, therefore losing part of their profits and having less capital available to invest in R&D. Thus, the overall net effect is not univocal and depends on the state of the company before engaging in international trade. For the initially more productive firms of Aghion *et al.*'s (2018) sample (meaning with productivity above the median), the net effect was positive: the competition of the incumbent had a relatively low effect and was more than compensated by the increase in demand. Instead, for less productive firms, the positive variation in revenues was not sufficient to cover the loss of profits due to the tough competition of the foreign incumbent. In addition to this finding, the research showed another important result: innovating firms of the sample are concentrated among exporters and non-exporting innovators are similar to non-exporting non-innovators. Moreover, "non-exporting innovators do not look very different than non-exporting non-innovators, and the various measures of firm size (employment, sales, value-added) respectively for innovators and non-innovators among non-exporters remain close to each other" (Aghion *et al.*, 2018, p. 19).

2.1.2 Relationship between import and innovation

2.1.2.1 Theoretical effects of import on innovation

Before reporting the results (sometimes contrasting) of past empirical analyses, we would like to do a brief review of the expected theoretical effects that an increase in import volumes can have on the innovation performance of companies of the domestic country.

Here below, we briefly show the main possible effects of a positive variation in the imports on domestic innovation, before explaining them all in detail.

Table 2: Main theoretical effects of import on innovation.

	Effect	**Rationale**
	Positive	Shorter product life cycle → firms fostered to update their products.
"Displacement effect" (or "escape competition effect")	Positive	Reduction of pre-innovation rents.
"Schumpeterian effect"	Negative	Reduction of post-innovation rents.
"Market-expansion effect"	Positive	Fixed costs are spread in a larger market → more resources available for innovation.
	Positive	Knowledge embodied in imported goods.
"Preference effect"	Positive	Managers' job threatened by competition → more effort to innovate.

Without any doubt, an increase in imports makes also competition increase, and the *Oslo Manual 2018* (OECD/Eurostat, 2018) suggests that intense competition can result in short product life cycles. Consequently, firms are fostered to update their products frequently, resulting in a high rate of product innovation.

Some researchers also claim that lowering import barriers, by increasing competitive intensity, could reduce agency costs (Bloom *et al.*, 2016; Schmidt, 1997), increasing the incentive to gain market share (Bloom *et al.*, 2016; Raith, 2002) or lowering cannibalization of existing profits. This is called by Arrow (1962) "displacement effect". It shows up in different guises in Aghion *et al.*'s (2005) or Shu and Steinwender's (2019) "escape competition effect" and the "switchover costs" of Holmes *et al.* (2008). In other words, imports are a source of competition and competition could increase incentives to innovate by reducing the pre-innovation rents, that is, the rents a firm can capture without innovating (Aghion *et al.*, 2005; Arrow, 1962; Bloom *et al.*, 2016; Shu and Steinwender, 2019). That is because competitive pressure leads to a reallocation of the market shares among domestic firms with different technological capabilities and firms react to competitive pressure by innovating, because otherwise they may further lose market share and profit (Gonchar and Kuznetsov, 2018; Wang and Blomström, 1992; Lu and Ng, 2012).

The second possible effect has an opposite impact on innovation: due to its nature, competition could dissipate the price-cost margins (and consequently also profits), thereby reducing potential rents that a firm could capture from innovating (Aghion *et al.*, 2005; Aghion *et al.*, 2018; Bloom *et al.*, 2016; Shu and Steinwender, 2019; Schumpeter, 1942) and this mechanism is called "Schumpeterian effect", or, by Aghion *et al.* (2018), "competition effect", which predicts that import competition has a negative impact on firm innovation. Indeed, economic perspectives examine why organizations innovate and which forces drive innovation (OECD/Eurostat, 2018). At this regard, Schumpeter's (1934) theories see innovation as a solution when searching for new opportunities and competitive advantage over current or potential competitors. The combination of these two effects is consequently ambiguous (Aghion *et al.*, 2005; Bloom *et al.*, 2016). However, models were developed which can show that the escape-competition effect dominates on the Schumpeterian effect "when competing firms are neck-and-neck in their levels of technological advancement, whereas the Schumpeterian effect dominates for the laggards who are far behind the leaders at the technological frontier and have a low chance of catching up" (Shu and Steinwender, 2019, p. 45). Another explanation why laggards may not react to imports with innovation is that they become more *constrained*: as it will be reported in the next paragraph, firms may decide to innovate less, not because innovation per se would not have a positive net value for the company, but because the firm may not be able to have access to enough credit to invest in innovation (Hombert and Matray, 2018; Shu and Steinwender, 2019).

A second group of innovation models stresses the importance of trade in increasing market size and pushing innovation through this market expansion effect (Bloom *et al.*, 2016; Krugman, 1980; Schmookler, 1966). Lower trade costs enlarge the market size over which to spread the fixed costs of the investments in innovation (Bloom *et al.*, 2016; Lileeva and Trefler, 2010).

A third driver affecting national innovation through imports is the fact that innovation could enable domestic firms to access better overseas' knowledge (Acharya and Keller, 2008; Bloom *et al.*, 2016; Coe and Helpman, 1995). According to the innovation system theory, the innovation process involves many interactions and feedbacks in knowledge creation and use and is based on a learning process with multiple inputs (OECD/Eurostat, 2018). Such learning process may be allowed through the import of intermediate inputs (Bloom *et al.*, 2016). However, such mechanisms do not seem to be appropriate in the Chinese context, since European firms have (currently) a technological lead over China. Indeed, Gonchar and Kuznetsov (2018) define imports as "a source of technological knowledge, embodied in machinery, equipment, and intermediates" (p. 504). The literature suggests import-related intra-industry improvements in firm technologies and better product mix, resulting from higher variety and quality of the inputs (Damijan *et al.*, 2014; Goldberg *et al.*, 2011; Gonchar and Kuznetsov, 2018). "New knowledge may materialize in innovation through copying, imitation, reverse engineering, and improvement of human capital, as well as upgrading of production technologies" (Gonchar and Kuznetsov, 2018, p. 504).

The agency literature introduces another perspective thinking about the impact of competition on innovation, which Shu and Steinwender (2019) label as "preference effect". Managers responsible for choosing how much to innovate may not make the choice that maximizes profits of their firm and may pursue instead private benefits simply deriving from their firm's continued existence (Hart, 1983; Raith, 2003; Schmidt, 1997; Shu and Steinwender, 2019; Vives, 2008). When increased competition threatens the existence of their business, and consequently their job, they may put more effort and innovate just to avoid losing such private benefits. Some related literature shows that competitive pressure reduces managerial slack in firms (Holmes and Schmitz Jr, 2001; Leibenstein, 1978; Martin, 1978; Martin and Page, 1983; Shu and Steinwender, 2019). The preference effect implies that import competition has a positive impact on firm's innovation (Shu and Steinwender, 2019). Anyway, the preference effect is less likely to activate in initially more productive firms, since they face lower bankruptcy risk (Shu and Steinwender, 2019).

An ambiguous impact on innovation could occur when importing inputs. Having access to imported intermediate goods may lower input costs, increase the quality of inputs, or improve the efficiency of the whole production process (Bøler *et al.*, 2015; Halpern *et al.*, 2015; Shu and Steinwender, 2019). Thus, an importing firm may produce new or higher quality outputs (Bas and Strauss-Kahn, 2015; Fieler *et al.*, 2018; Goldberg *et al.*, 2010; Shu and Steinwender, 2019). It may also innovate more thanks to higher profit margins or more opportunities to learn about new product design, new production processes, new materials or technologies, or new organizational methods (Coe and Helpman, 1995; Ethier, 1982; Grossman and Helpman, 1991; Markusen, 1989; Rivera-Batiz and Romer, 1991; Shu and Steinwender, 2019).

In addition, efficiency and product innovation gains can come from imports due to cost reductions and scale effects, when better price-quality ratios of imported inputs (in comparison with domestically produced intermediates) complement and expand the range of available inputs. Lower import tariffs play a similar cost-saving role (Colantone and Crino, 2014; Gonchar and Kuznetsov, 2018).

At the same time, "access to imported intermediates may decrease innovation by reducing the need for process-improving technologies" (Shu and Steinwender, 2019, p. 55).

Chakravorty *et al.* (2017) provide a theoretical model of imitation and innovation in which domestic firms that are engaged in competition react to import competition by deciding whether to invest in a higher quality product. The model "generates an inverted-U shaped response to competition: at low levels of imitation, domestic firms make higher profits and a rise in imitation triggers innovation. However, when import penetration is high, the effect of innovation on profits is weak and imitation reduces innovation" (Chakravorty *et al.*, 2017, p. 3). Anyway, in their analysis hypothesis that the domestic firm is able to cover the fixed cost of innovation is implicit (Chakravorty *et al.*, 2017).

2.1.2.2 Past empirical findings in different geographical and organizational contexts

Many researchers are precisely focused on the effect of import flows on innovation, in different organizational and, more often, geographical context. Some of them keep a broader point of view, other ones specifically investigate the effects of importing from low-wage countries, including China.

Chang *et al.* (2013) did their analysis on a broad-focus basis, investigating the impact of engagement trade in general with other countries by companies of OECD countries on their innovation (measured with patent counts). "Globalization", from an economic point of view, "refers to the cross-border movements of goods, funds, personnel and information" (Chang *et al.*, 2013, p. 329) and international trade could be expected to give origin to technology spillovers (Branstetter, 2006; Chang *et al.*, 2013; Coe and Helpman, 1995; Coe *et al.*, 1997; Coe *et al.*, 2009; Cohen and Levinthal, 1989; Geroski *et al.*, 1993; Keller, 1998; Keller, 2004; Kneller, 2005; Madsen, 2007; Mancusi, 2008 Liu and Zou, 2008). Specifically, the channels that were analyzed were outward direct investment (ODI), inward direct investment (IDI), cross-border mergers and acquisitions (M&A) by foreigners (included in IDI), R&D expenditure, exports, and imports.

The results showed a positive significant relationship of exports and ODI with the domestic country's patents, while IDI (including cross-border M&A by foreigners) exhibited a negative relationship with domestic patents. Foreign R&D expenditure was deferred of one period, just because the effect of the expenditure cannot of course be seen immediately on innovation. This variable had a significant and positive impact on the number of patents, which confirmed the deferred nature of the impact of the R&D input on the patents. Imports, instead, were found not to have any significant effect on technology spillovers.

Gonchar and Kuznetsov (2018), on the other hand, analyzed Russian manufacturing context and suggested past studies which found empirical evidence of imports contributing to growth and innovation, since they are a critical source of knowledge spillovers, and decided to "investigate the link between a firm's engagement in imports and its learning from imports in order to innovate" (Gonchar and Kuznetsov, 2018, p. 502). Gonchar and Kuznetsov's (2018) literature review suggests that imports may boost innovative activities, "primarily through the import of knowledge embodied in imported capital goods and intermediates", then "through complementarity between adopted foreign knowledge and domestic competences, especially complementarities of trade with skill, R&D, technology position relative to the frontier and favorable geographical location. Finally, import competition may increase the incentive to innovate" (Gonchar and Kuznetsov, 2018, p. 505).

In the empirical analysis, the authors made surveys regarding key features of the companies, and of course their type of trade and innovation and they controlled for differences between the markets where firms operated and were located.

Their findings show beneficial effects of import on innovation and learning effects of imports appear to be higher for product - than for process innovation. In addition to this, "import-innovation link may be stronger for scale-efficient firms that display technological advantages, enjoy a favorable location, and operate on product markets, which are characterized by strong import competition" (Gonchar and Kuznetsov, 2018, p. 502). Indeed, importing firms are found to be "significantly more innovative than firms that rely on domestic sources of capital investment and inputs, while the transfer of embodied knowledge stimulates technological progress by creating incentives to introduce product and process innovations" (Gonchar and Kuznetsov, 2018, p. 521). However, the effect is not homogeneous: as suggested by previous authors (Damijan and Kostevc, 2018), also Gonchar and Kuznetsov's (2018) evidence confirms that firms that are closer to the technology frontier are more likely to benefit from importing, at least for process innovations.

On the other hand, importing does not assure a booster for innovation performance: some firms fail to innovate after being active in importing, due to lack of efforts on in-house R&D or because the pressure they face from import competition is apparently not tough enough (Gonchar and Kuznetsov, 2018).

The previously mentioned Damijan and Kostevc (2015) tested the relationship between international trade (import and export) and innovation. A survey was made on a sample of Spanish manufacturing firms asking information about product and process innovation and R&D expenditure, also controlling for the size of the firms and for their distance from technology frontier. Consistently with previous research (Damijan *et al.*, 2010), the authors claim that "learning from trade is associated with firm innovation activity" and that "firms with extensive importing links are more likely to introduce new products or processes" (Damijan and Kostevc, 2015, p. 409). Indeed, results show a positive relationship between internationalization and innovativeness, and "firms closer to the relevant technological frontier are more likely to benefit from this learning processes through internationalization" (Damijan and Kostevc, 2015, p. 433). Results also indicate that import links specifically are important for smaller firms to start learning the production processes and to improve their product characteristics. This may help them to get ready and acquire the know-how that it takes for their entry into foreign markets with their products (Damijan and Kostevc, 2015).

Shu and Steinwender (2019) investigated what the impact of importing from abroad could be on innovativeness of companies in different parts of the world. They found out, in accordance also to other studies we mentioned, that such impact depended on the and the national distance (and that of the company) from the technology frontier. The overall effect was negative for laggards that were still far from the frontier, while it pushed innovation performance of firms which were at the same point in the technological advancement comparing to competitors. Indeed, the Schumpeterian effect was larger than the escape-competition one for the first type of firms we mentioned, meaning that innovating is not sufficiently beneficial, in terms of reducing the damages of competition, if the company is too far from the technology frontier. On the other hand, in the latter type of firms, the

Schumpeterian effect is more than compensated by the escape-competition one, and more technologically advanced firms are likely to benefit from innovation (Aghion *et al.*, 2005; Shu and Steinwender, 2019). In addition to this, the preference effect also depends on the capabilities of the company: since the threat of the competition is more about less-productive firms, the preference effect is less likely to occur in highly productive firms.

From a geographical perspective, results were found to be significantly positive in developing countries and in Europe: firms had to face less competition, higher managerial slack and more frictions in the market. Findings were, instead, mixed in North America, since there was the highest initial competition, the lowest risk of managerial slack and less frictions in the market (Aghion *et al.*, 2005; Shu and Steinwender, 2019).

Anyway, the effect of imports on innovation also occurs through competition, but the latter depends on the tariffs imposed in each firm's own industry (Amiti and Konings, 2007; Shu and Steinwender, 2019; Topalova and Khandelwal, 2011).

On the other hand, Andrijauskiené and Dumčiuviené (2019) analyzed the effect of international trade on innovation in all the 28 EU member states. They built several models, each one with a different dependent variable representing innovation. For the definition of the variables, they based their starting point on Villa's (1990) concept of NIC (National Innovative Capacity), defined as the "changes in technology, invention (ideas that are patented) and the competitiveness of economic activities" (Andrijauskiené and Dumčiuviené, 2019, p. 573) and the variables were exactly the most widely used indicators for NIC. The NIC output indicators were used as dependent variable of each model: community design (CD) applications per million inhabitants, European Union trademark (EUTM) applications per million inhabitants, patent applications to the European Patent Office (EPO) by priority year per million inhabitants, exports of high-tech products (% of GDP)[3]. The NIC input indicators were used as independent variables for the models: gross domestic product (GDP) (euro per capita), population having tertiary education (levels 5-8) (% of population), total public expenditure on education (% of GDP), employment in high-technology sectors (high-technology manufacturing and knowledge-intensive high-technology services) (% of employment), imports of goods and services (% of GDP), imports of goods (% of GDP), imports of services (% of GDP), imports of high-tech products (% of GDP), intramural R&D expenditure in the business sector (% of GDP), intramural R&D expenditure in the public sector (% of GDP)[4]. One shortcoming of the NIC output indicators is that they are not much suitable for innovation in services (Andrijauskiené and Dumčiuviené, 2019; Hipp and Grupp, 2005).

[3] Source for the cited study: Eurostat Database (Eurostat 2018), EIS Database (European Commission 2018).
[4] Ibidem.

The "results prove that an international transmission of knowledge through import spillover boosts a number of innovative outputs (design applications, trademark applications, and exports of high-tech products), and is even more important than direct expenditures on education or investment in R&D" (Andrijauskiené and Dumčiuviené, 2019, p. 579). Nevertheless, an unexpected result was also found: the relationship between the patent application count and imports turned out to be negative, although, "logically, import of goods and services should provide access to new technologies and knowledge, helping to develop innovative capabilities of a country" (Andrijauskiené and Dumčiuviené, 2019, p. 581). Anyway, the international transmission of knowledge of imports requires and depends also on the absorptive capabilities of the country (Andrijauskiené and Dumčiuviené, 2019; Huang *et al.*, 2010).

The Dutch context was examined by Vancauteren *et al.* (2019), who investigated how imports from the rest of the world affected innovation in the Netherlands, through the empirical analysis of a 2400-firms sample. Citation-weighted patents were used as proxy for innovation, employing data on patent applications, both on Dutch level (to capture the data about SMEs) and on European level (to get data about larger companies). This was made in order to control for firm heterogeneity in patent activity related to firm size and economic international activity. The number of citations was taken into consideration to discover whether the quality of the patents was also affected by the international trade.

Their "results show that higher import competition in the Netherlands has a negative impact on the probability that a firm applies for a European patent and a negative impact on the number of patent applications as well" (Vancauteren *et al.,* 2019, p. 26). However, it has no influence on the quality of the patents: when import competition increases, the number of citations does not increase or decrease significantly. This finding is important to reveal that the response is heterogeneous across firms of different innovation activities, suggesting that, the more quality-driven innovative firms are, the more able they are to catch the benefits of import competition.

Some authors focused their research on a more specific question: they analyzed the impact on innovation caused by the increasing import from low-wage countries, especially China. Low-wage countries are defined as those which have a per capita GDP lower than 5% of that of the United States during the period between 1972 and 1992 (Bernard *et al.*, 2006; Chakravorty *et al.*, 2017).

"The rising share of manufacturing imports into the US from low-wage countries increased from 4.6% in 1990 to 12.2% in 2001, thanks to a substantial contribution by products made in China" (Chakravorty *et al.*, 2017, p. 2), the major contributor of this share.

Chinese comparative advantage concerns manufacturing industrial goods and China's rapid catch-up in terms of economy (due also to a prior large gap during the isolation under Mao (Autor *et al.*, 2016; Brandt *et al.*, 2014; Zhu, 2012)) represented a global supply shock for manufacturing and a global demand shock for raw materials (Autor *et al.*, 2016). China joined the WTO in 2001 and previous barriers to exports (expressly forbidden by WTO) were removed. In this period, in Chinese industries there was a shift from less-productive state-owned companies to private ones raising productivity and output (Autor *et al.*, 2016; Hsieh and Song, 2015).

The result was the beginning of an era of tough import competition suffered by US and European companies, which also caused a differential decline in manufacturing employment. Only Germany partially offset this by increasing exports to Eastern Europe, following the increasing imports from this area (Autor *et al.*, 2016).

Anyway, authors claim also that China "is moving beyond the period of catch-up associated with its market transition and becoming a middle-income nation" (Autor *et al.*, 2016, p. 37). Real wages are increasing quickly and indicate that Chinese cheap-labor era is coming to an end (Autor *et al.*, 2016; Li *et al.*, 2012) and that this will be in a future no longer its source of comparative advantage (Autor *et al.*, 2016).

Researchers decided to focus the empirical study on the effect of imports from low-wage countries, especially China, on innovation activities of a sample of US manufacturing firms. Many of them used firm patent applications (first with and then without adjusting for citations) as measures of innovation (Chakravorty *et al.*, 2017; Cohen, 2010; Griliches, 1990).

The findings of Chakravorty *et al.* (2017) show a positive robust relationship between exposure to imports from China and innovation activities of US manufacturing firms when innovation is measured by the number of citation-weighted patent applications. Without adjusting for citations, no significant relationship was found. This means that it was not the number of patents increasing in response to import from low-wage countries, instead it was the quality: US manufacturing firms do not produce more patents, they produce more "valuable" patents.

Next, they study how heterogeneous the impact of Chinese import competition is across different industries and firms and find out that US firms in low-tech and in less-differentiated industries are more incentivized to innovate in response to imports from China. That is supposed to be because such companies are not easily able to differentiate their products from their competitors with lower wage costs, thus they face a more intense competition with respect to those operating in high-tech or highly differentiated industries (Amiti and Khandelwal, 2013; Chakravorty *et al.*, 2017). Moreover, results show that US firms with high capital intensity and low labor productivity innovate more when they face import competition from China. Such companies may be able to react faster to the rising imports from low-wage countries, either thanks to their advantage in reallocating resources towards innovation, or just because they are hit harder than more efficient domestic producers. (Bloom *et al.*, 2021; Chakravorty *et al.*, 2017). In their study, Chakravorty *et al.* (2017) control also for year or firm specificities, by adding two dummy variables in the model, to eliminate any other potential impact on innovation. The important key point to be highlighted from the research is that, according to this analysis, "import competition affects the quality of patent production, not the volume" (Chakravorty *et al.*, 2017, p. 22).

Other researchers investigated this question precisely in specific countries, for instance, Autor *et al.* (2020) analyze the impact of import exposure from China on US manufacturing firms between 1991 and 2007, before and after China joined the WTO. Innovation was proxied both by R&D expenditure and by patent counts, and the study shows a negative significant impact of imports on both these variables. More specifically, the authors found that such negative effect was larger for firms with larger indebtedness, less profits, a lower sales/worker ratio and lower capital/worker ratio.

On the other hand, Bloom *et al.* (2016) found a positive significant effect in the European context. The analysis was developed on a panel of twelve European countries between 1996 and 2007. Their findings show that, *within* firms that were more exposed to imports from China, the absolute volume of innovation (represented by the number of patents) increased. Secondly, higher-tech firms appear to be somehow protected from Chinese imports and "in sectors more exposed to Chinese imports, jobs and survival rate fell in low-tech firms (e.g., lower patenting intensity)" (Bloom *et al.*, 2016, p. 28), while high-tech firms are relatively sheltered (*between* firm reallocation effect). "Both within and between firm effects generate aggregate technological upgrading" (Bloom *et al.*, 2016, p. 29).

Yamashita and Yamauchi (2020) focus their study on the Japanese context, investigating both domestic and global firms first in 1995 and then in 2005, a few years after China joined the WTO. The number of patents was used as a proxy for innovation, although this time it was controlled for the quality of them, by adding the number of citations per patent in the model. The number of patents was found to be larger, after the exposure to import competition from China, in many high-tech industries, such as electronics. This effect was even larger in the panel that included global firms: they are larger in size and it is reasonable to expect that this allows them to have more resources to dedicate to innovation. Anyway, while the absolute volume of patents increased, the average quality of such patents declined: the total count was inflated by a large number of patents for incremental innovations (represented by patents with a number of citations equal to zero). Such finding is likely to indicate that Japanese firms strategically increased patenting activity "as a defensive move to protect their core technologies from greater Chinese imports" (Yamashita and Yamauchi, 2020, p. 63). Defensive patenting clearly shows that companies, in some cases, are more interested in protecting their intellectual property than in truly innovating (Yamashita and Yamauchi, 2020).

Another example is Dang's (2017) study set in Vietnam. The author studied the effect of the import penetration of China in the Vietnamese input manufacturing market (most of the imported products involve raw materials for future finished Vietnamese export goods) after Vietnam and China signed a series of trade and economic agreements.

Dang (2017) constructed a firm-level Chinese import penetration measure taking into account both imports from China and from the rest of the world. For the output variable, Dang (2017) used a survey asking questions about various types of innovation activities: product innovation, process innovation, and product improvement. The main explanatory variable, representing the imports, was lagged of one period, since it's reasonable to expect that firm innovation does not immediately react to trade shocks. Two dummy variables are also included in the model, like in models developed by other researchers, in order to control for firm- and year-specific effects. In order to also control for observable determinants that could be correlated with both import and innovation variables, other variables (after a logarithmic transformation) were included: firm value added, firm wage bill, firm gross profit, firm domestic sale, firm employment, and firm's proportion of unskilled workers.

Final results show a negative statistically significant relationship between import penetration and technological improvement, although the coefficient is quite small. Such findings "support the hypothesis that domestic firms do not need to innovate as cheap imported inputs allow them to invest less in innovation. Another possible explanation is that most Chinese imports are complementary rather than substitute goods in relation to domestic products" (Dang, 2017, p. 8). Thus, they do not create pressure on domestic firms to start being active in innovation (Dang, 2017).

Iacovone *et al.* (2011) examined innovation of Mexican firms in response to increased competition from China between the years 1998 to 2004, which include China's entry into international markets, by becoming a member of WTO in 2001. This event was defined by some researchers (Bloom *et al.*, 2016; Krugman, 2008; Winters and Yusuf, 2007) as the largest trade shock during the last 30 years. China gained new market access, and her already high rates of export growth accelerated even more.

Differently from the majority of the other studies that address this question, Iacovone *et al.* (2011) do not take into account technology investments as a proxy for innovation, but they analyze specific organizational changes of the firms, namely total quality management, statistical quality control, quality control, Just-in-Time system, re-organization, and job rotation. Indeed, the model includes a variable that denotes the type of innovation introduced. Another additional variable instead represents the specific characteristics of the company.

Findings show that the aggregate level of innovation of Mexican manufacturing firms (which overlapped in terms of products with imports from China) did not change much with the new import competition from China (Iacovone *et al.*, 2011). Nevertheless, "relatively productive firms innovate more in response to the China trade shock, while less productive firms innovate less. Import competition sharpens the difference between strong and weak performing firms because it leads to innovation that amplifies the initial difference" (Iacovone *et al.*, 2011, p. 3), since productive firms had more to gain from innovation comparing to less productive firms. Such difference is the strongest for Just in Time (Iacovone *et al.*, 2011).

"The mixed evidence on this question […] suggests that firms may cut R&D investment not because its NPV becomes negative, but because trade shocks increase frictions such as credit constraints" (Hombert and Matray, 2018, p. 2037).

Indeed, some research (Hombert and Matray, 2018) focuses specifically on testing the hypothesis of R&D investment as a shield for import competition: they test weather firm performance (measured by sales growth or profitability) is less adversely affected by an increasing import competition when the firm has invested more in R&D before such increase. The analysis is set in the US, in a time when US government changed its tax policy, giving tax credits to the companies. Priorly to this regulation change, credit constraints forced companies to cut their R&D expenditures, since such an investment would have been impossible from a cash-flow point of view, and the result was a lower productivity growth (Aghion *et al.*, 2012; Hombert and Matray, 2018). The research investigates the effect of China's import penetration on companies, also on those which exploited the tax credits investing in R&D. The rising imports led to slower sales growth and lower profitability for firms in import-competing industries, but the results show that "this effect is significantly smaller for firms that have invested large amounts in R&D thanks to generous R&D tax credit policies" (Hombert and Matray, 2018, p. 2037). The impact of R&D on firm performance comes mostly through a higher product differentiation (Hombert and Matray, 2018; Sutton, 1991) and the research shows that, as a result of a higher performance, "R&D-intensive firms can avoid downsizing and continue to invest in capital and labor despite being exposed to trade shocks" (Hombert and Matray, 2018, p. 2037). Anyway, "the effect of the interaction between impact of import competition and R&D tax credit on firm performance is also relevant outside the United States as most high-income countries have introduced such tax credits to promote innovation" (Hombert and Matray, 2018, p. 2037).

Here below, we report a summary of the main studies we mentioned that focus on the impact of trade flows from and to China or low-wage countries in general on national innovation.

Table 3: Summary of the main studies mentioned in the literature review that focus on the impact of trade flows from and to China or low-wage countries in general on national innovation. For each study, authors, year of publication, geographical setting, period of analysis, variables, estimation method, and resulting impact are reported.

Authors, year	**Geographical setting**	**Period**	**Variables**	**Method**	**Results**
Autor *et al.*, 2020	US	1991-2007	**Input**: change in input exposure; sectorial control variables. **Output**: change in patents by US relative to mid-period patents.	Difference in differences.	Negative
Bloom *et al.*, 2016	12 European countries	1996-2005	**Input**: change in % import from China relative to world. **Output**: change in *ln(patent)*.	OLS and IV.	Positive
Chakravorty, 2017	US	1990-2006	**Inputs**: import penetration from China; lagged of 1 controls (R&D intensity, patent stock, *ln(No. employees), ln(capital intensity), ln(NOI*[5]*))*. **Output**: patent applications.	Two OLS regressions: with and without weights for patent applications.	Positive
Dang, 2017	Vietnam	2011-2015	**Inputs**: Chinese import penetration (lagged of 1); year- and firm-specific dummies. **Outputs**: new technology adoption; new product development; improvement to existing product.	Regression instrumented with global exports.	Slightly negative
Iacovone *et al.*, 2011	Mexico	1998-2004	**Input**: change in import competition from China. **Output**: specific type of innovation.	8 OLS regressions with 8 types of innovation as *y*.	Positive

[5] NOI: Net Operating Income.

Vancauteren *et al.*, 2019	Netherlands	2000-2010	**Inputs**: change in import competition from China (lagged of 1); *ln(R&D)* (lagged of 1); *ln(No. employees).* **Output**: citation-weighted patent applications.	Static random effects Hurdle model controlling for zero inflation.	Negative
Yamashita and Yamauchi, 2020	Japan	1995-2005	**Input**: change in Chinese import penetration. **Output**: change in No. patent applications.	Regression instrumented with imports from China by 8 other countries.	Positive

2.2 Research question

What emerges from the literature review is that the results of past empirical analyses and the theoretical predictions of possible impacts of imports on innovation remain ambiguous.

There's no doubt that importing from other countries raises the competition faced by firms in the domestic area, but competition, in turn, could either stimulate the companies and push them to innovate, or reduce ex-post innovation rents, lowering profit-cost margins and leaving them with less resources available for investing in R&D.

Other considerations take the knowledge spillover and its positive impact on innovation and improvement of products and processes into account, thanks to information and knowledge embodied in manufacturing products.

Managerial personal interests or firm's inertia facing an already high-quality product, in which other countries are specialized, can also be the mean by which innovation performance is affected, positively or negative, by a positive variation in imports.

Many geographical contexts have been analyzed, mainly the US, although some analyses were set in Europe or in specific Asian countries.

Specifically, some research does not analyze the impact of imports in toto, but only imports from China. On this specific part of the topic, literature was revised about analyses set mostly in the US or in other specific countries: that can be a limitation of the reliability of the results, since they may be distorted by specific aspects of the country the analysis is set in.

One of the studies (Bloom *et al.*, 2016) is set in an area that includes twelve European countries, but does not take US context into account, which is the country where China currently exports most.

In addition to this, we found that no study on this specific topic has a broader horizon than ten-twelve years. Past analyses were stopped around 2007 and do not take later important years into account. A longer time series can surely make an analysis more reliable (ceteris paribus); we would also like to investigate whether including fourteen or fifteen more recent years, in which technology evolved a lot, and this can help us to better understand the trends and the correlation in the phenomenon we want to analyze.

3. Empirical analysis

In this Section, we describe the empirical analysis in detail.

In Section 3.1, we illustrate the data collection process and our methodology: starting from the description of the sample and the sources where we got all our data, we describe in detail the collection of the data and the composition of our dataset, how we coped with any inconveniences during the collection phase, the choice of the variables, including the controlling ones. Lastly, we illustrate the econometric method we used to proceed with our analysis.

In Section 3.2, we provide the main descriptive statistics and the econometric results.

In Section 3.3 such results will be discussed.

3.1 Data collection and methodology

3.1.1 Sample and sources

We decided to set the start of the period of our analysis in 1995, a few years before China entered the WTO, to see how the time series of our variables looked like before the event that originated the raise in international trade flows from and to China. The last year of our analysis is 2019: our objective was to analyze data and investigate for trends and causalities in as recent as possible period. However, data about year 2021 were not available at the moment in which we collected our data. We also decided to exclude 2020 from our sample: due to the start of the global pandemic COVID-19, consequences affected most of the aspects of the reality, including trade.

We decided to analyze the phenomenon in the OECD context (like for example Barbosa and Faria (2011) and Chang *et al.* (2013) did), including the EU15 countries[6] (a few more

[6] Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain, Sweden, UK, US. Source: OECD Glossary of statistical terms.

countries than those in Barbosa and Faria's (2011) analysis of the importance of institutions in affecting innovation). We excluded Luxembourg from the group, since its geographical, and consequently volume, dimensions are not as much relevant as those of the other countries in the sample, and we added the United States, due to their large dimensions and large volumes of goods traded with China.

With T=25 years and N=15 countries of analysis, our sample comes out to include a total of 375 units of analysis, getting reliable enough in terms of numerosity.

Our dataset was composed by reporting data from different databases on an Excel file, where data were firstly elaborated.

Some data were interpolated because they were not available in the databases where we got them. They were interpolated with different methods, according to the nature of the specific data and of the availability of such data, for example, in different years.

The data regarding import volumes, as in the analysis by Bloom *et al.* (2016), were taken from the UN Comtrade International Trade Statistics Database[7].

As we will better deepen later, we chose data on patents and trademarks to measure innovation performance and the source we used was the WIPO IP Statistics Data Center[8].

In order to elaborate our data more precisely (like Barbosa and Faria (2011)), we also got information about population counts and GDP, which were extracted from the database of the World Bank's World Development Indicators[9].

3.1.2 Dependent variables

In order to measure innovation output at country level, we collected data about patents and trademarks.

Data about intellectual property rights, especially patent counts, are relatively easy to collect, in comparison to the other measure for innovation performance. Moreover, although data about R&D expenditure would be not much difficult to collect, such a measure as output variable would still have limitations that, in our opinion, would bias our work more than those of the IPR counts. As we deepened in the literature review, R&D expenditure, as a measure for innovation, does not take into account that such an input (which is also not the one and only input for an innovation (Kleinknecht *et al.*, 2002; Makkonen and van der Have, 2012;

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[7] UN Comtrade International Trade Statistics Database: https://comtrade.un.org/
[8] WIPO IP Statistics Data Center: https://www3.wipo.int/ipstats/
[9] World Bank's World Development Indicators: https://databank.worldbank.org/source/world-development-indicators#

Ratanawaraha and Polenske, 2007)) does not necessarily result in an actual successful innovation (Acs *et al.*, 2002; Gu and Tang, 2004; Nelson, 2009; Makkonen and van der Have, 2012). Patent counts are also only applicable to goods and not to services (Andrijauskiené and Dumčiuviené, 2019; Camacho and Rodríguez, 2005; De Liso and Vergori, 2017; Hipp and Grupp, 2005; Makkonen and van der Have, 2012).

Lastly, we expect high-tech sector to be the one characterized by the highest amount of IPRs. That is also why our measures for innovation performance seem to be suitable for this setting.

Here below we report a list of the data we included in our dataset. We got them all from the WIPO IP Statistics Data Center, selecting 1995-2019 as year range and the 15 countries of our sample as origin[10].

The first patent count we needed was represented by the indicator "Total patent applications (direct and PCT national phase entries)" in the WIPO IP Statistics Data Center[11] in the report type "Total count by applicant's origin" and it was indicated as *pat* in our dataset.

In addition to this, we included a second patent count, specifically focused on the high-tech sector, and it was represented by the indicator "Patents publications by technology"[12] in the report type "Total count by applicant's origin". Among the available fields, we selected those concerning digital technologies[13]. The count was indicated as *tech* in our dataset.

Next, we included data about the trademarks, those associated with the indicator "Total trademark applications (direct and via the Madrid system)" in the WIPO IP Statistics Data Center[14] and they were indicated as *tm* in our dataset.

We also retrieved data about the population of the countries from the World Bank's World Development Indicators (indicator: "Population, total"). Then, we calculated the ratios between our patent and trademark variables and population, in millions of inhabitants, to account for country size. Namely, we got the following per-capita values: *patpop, techpop, tmpop*.

[10] In the WIPO IP Statistics Data Center, the origin indicates the country applying or registering an intellectual property right, such as a patent, a trademark, or an industrial design.
[11] In the WIPO IP Statistics Data Center, it's indicator number 1.
[12] In the WIPO IP Statistics Data Center, it's indicator number 4.
[13] The fields of technology that were selected are the following (associated with their number in the WIPO IP Statistics Data Center list:

2: Audio-visual technology;
3: Telecommunications;
4: Digital communication;
6: Computer technology;
8: Semiconductors;

[14] In the WIPO IP Statistics Data Center, it's indicator number 1.

Since patent and trademark flows are rather volatile across years, as common in the innovation literature, we decided to transform the original data into stock values using the permanent inventory method. Specifically, we calculated the stock of variable *X* at time t in this way:

$$stockX = X_{t-1}(1-\delta) + X_t$$

where δ is the yearly depreciation rate of the patents which we set at 15% (Hall *et al.*, 2005; Simeth and Cincera, 2016). Our dependent variables are labelled as follows: *stockpatpop*, *stocktechpop*, and *stocktmpop*.

3.1.3 Explanatory and control variables

The main input variable is the one measuring the volume of imports from China: the goal of this analysis is to investigate the impact of such variable on domestic stocks of IPRs. Data for imports come from the UN Comtrade International Trade Statistics Database. The values are all expressed in US dollars (USD) and those we chose for our sample include imports of all types of goods; the reporters we selected are the 15 countries of our sample (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain, Sweden, UK, and US) and the selected period is the timeline of our analysis (1995-2019).

The partner we selected for the main variable is obviously China and the variable has been named *impchinavol*.

We also got information about the same type of data, except for selecting the whole world as partner and we labelled these data as *impworld*. In fact, we also calculated the annual share of imports from China on total world's imports. This ratio between *impchinavol* and *impworld* is the actual Chinese import penetration, called *impchina* in our dataset[15].

As we explained in the literature review, institutions are defined as the rules of the game in a society (Barbosa and Faria, 2011; North, 1990). Thus, they influence each aspect of the actions of every entity belonging to such society, including companies, especially those "actions" which are more complex and have a larger impact on the environment, such as, for example, registering an intellectual property right. That is why high institutional quality is likely

[15] Some data about the imports were, however, not available: values of *impchinavol* and *impworld* for Belgium between years 1995 and 1998 were at first missing in our dataset, so we had to interpolate them. We solved our problem by replacing 1998 values first, thus we calculated $x_{1998} = x_{1999} - (x_{2000} - x_{1999})$, then those of 1997, 1996 and 1995, in sequence, as x_t (x_{1995}) as $x_t = x_{t+1} - (x_{t+2} - x_{t+1})$, keeping the same difference between subsequent years.

to facilitate and incentivize such phenomenon and affect its volume. We believe that variables concerning institutions fit good with analyses of innovation, when innovation performance is measured with patents or any other property right. In the literature review we mentioned studies setting institutional quality as explanatory variable to analyze changes in innovation (Barbosa and Faria, 2011; Taylor, 2009; Varsakelis, 2006; Zhu and Zhu, 2017): all of these works measured innovation performance basing their proxy on patents, no matter where the analysis was set. Also Cunningham *et al.* (2019) study the effect of legislation changes on innovation, measuring such output variable with the volume of patents. Following these reasonings, we chose to control for institutional quality in our analysis, including one more variable in the model as control factor. Such control variable (*Inst_Q*) is the average value the six WGI elaborated by the World Bank. Namely, they are: *voice and accountability* (*Voice_Acc* in our dataset), *political stability and absence of violence/terrorism* (*Pol_Stab*), *government effectiveness* (*Gov_Eff*), *regulatory quality* (*Reg_Q*), *rule of law* (*R_Law*), *control of corruption* (*C_Corr*)[16].

Then, we also added some other control variables, getting the data from the World Bank's World Development Indicators: namely, countries' GDP (*gdp* in our analysis), their R&D expenditure as percentage of the GDP (*rd* variable), and the value of their net inflows of FDI as percentage of the GDP (*nifdi* variable)[17].

3.1.4 Methodological strategy

To develop our analysis, we chose to use a panel dataset that is, "one which follows the same sample of individuals over time, and thus provides multiple observations on each individual in the sample" (Hsiao, 1985, p. 121). Such type of set seems to be valid and fitting with our kind of analysis. Indeed, many other authors we cited in our literature review analyzing the impact of imports on innovation (Andrijauskiené and Dumčiuviené, 2019; Bloom *et al.*, 2016; Chang *et al.*, 2013; Shu and Steinwender, 2019) set their research in panels of data.

[16] Worldwide Governance Indicators (WGI): https://info.worldbank.org/governance/wgi/Home/Reports .
Some values of the WGI were not available, so we interpolated them and we replaced the missing values by calculating the average value between that of the previous and that of the following year. Data about WGI were also missing for all the countries of the sample in year 1995. Since it was the first year of the series, and thus there was no value of the "previous year" available, we calculated such missing data x_t (x_{1995}) as $x_t = x_{t+1} - (x_{t+2} - x_{t+1})$ so $x_{1995} = x_{1996} - (x_{1997} - x_{1996})$.

[17] Some data related to the R&D expenditure were missing, so we interpolated them. Those of year 1995 were replaced by $x_{1995} = x_{1996} - (x_{1997} - x_{1996})$, those of year 2019 (last year of analysis) were replaced with an average of the previous 24 years (from 1995 to 2018), the others were replaced by an average of the previous and of the following ones, thus, in these cases, $x_t = \frac{(x_{t-1}+x_{t+1})}{2}$.

We found them appropriate for the investigation of the impact of imports on innovation, since both of them are likely to be affected by the specific year of analysis, and this bias can be eliminated, or at least limited, taking a whole time series into account. At the same time, both the phenomena (the variation in trade flows and in innovation) are also very likely to be affected by the geographical context (the country, in our case) in which they are set, thus, just taking a time series for a country would bias our analysis as well. As Hsiao (1985) stresses, panel data allow to combine benefits of both time series and cross-sectional data, and "to analyze, in depth, complex economic and related issues which could not have been treated with equal rigor using time series or cross-sectional data alone. Like cross-sectional data, panel data describe each of a number of individuals. Like time series data, they describe changes through time. By blending characteristics of both cross-sectional and time series data, more reliable research methods can be used in order to investigate phenomena that otherwise could not have been dealt with" (Hsiao, 1985, p. 122-123). From a diagnostic point of view, panel data could also, according to Hsiao (1985), reduce specification and multicollinearity problems.

The analysis was conducted with the use of the software Stata 17.

Summarizing, the variables that were used in our regression are the following:

Table 4: List of variables

	Name	**Full name**
Input variable	*impchina*	Import penetration from China
Control variables	*Inst_Q*	Quality of the institutions
	gdp	GDP
	rd	R&D expenditure / GDP
Output variables	*stockpatpop*	Total patent stock per population count
	stocktechpop	Total patent stock in the high-tech sector per population count
	stocktmpop	Total trademark stock per population count

3.2 Data analysis

3.2.1 Descriptive statistics

Just to catch one important aspect at a first glance, we calculated the average values of the imports from China per country from year 1995 to 2019 and it already shows that the US get the largest amount of imports among the countries included in our sample.

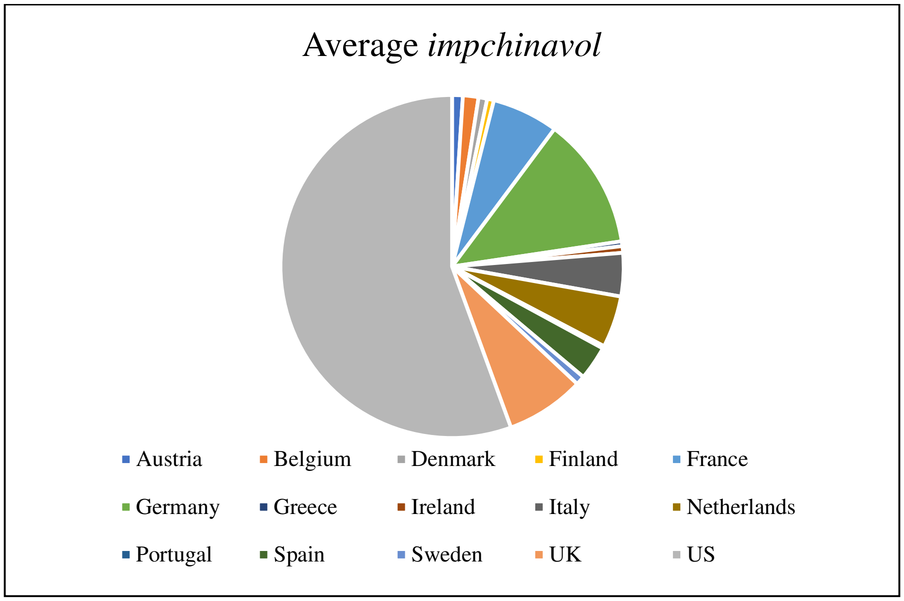


Figure 1: Total average imports from China by the 15 countries of the sample, divided among each one of them.

With the aim of looking for possible apparent trends of the main parameters during the entire time horizon and searching for maxima and minima, we calculated the average per year and per country of all such parameters (namely: *impchinavol*, *impworld*, *impchina*, *pat*, *tech*, *techpop*, *patpop*, *tm*, *tmpop*).

Here below we report the graphs[18] of the resulting average values per year.

[18] All graphs were made with the use of Microsoft Excel.

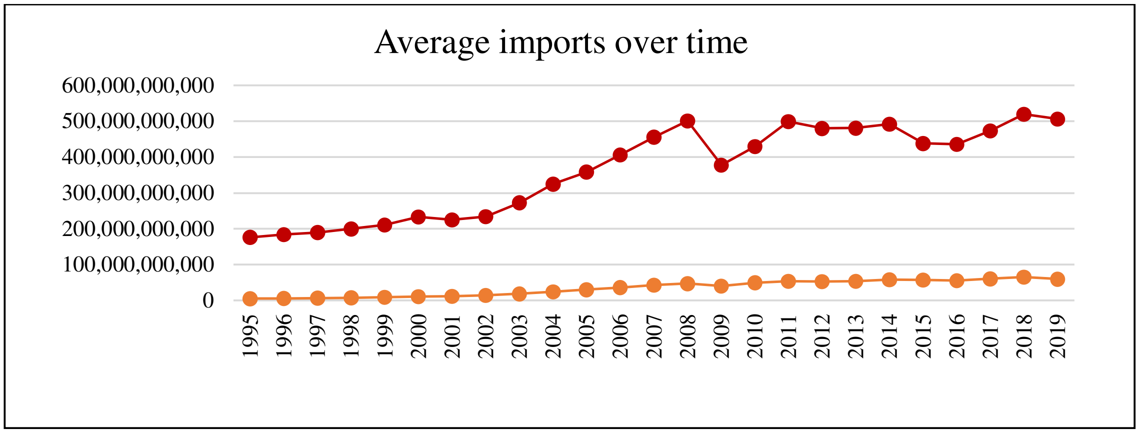


Figure 2: Graphs of the average values of *impchinavol* (orange bottom line) and *impworld* (red top line) per year.

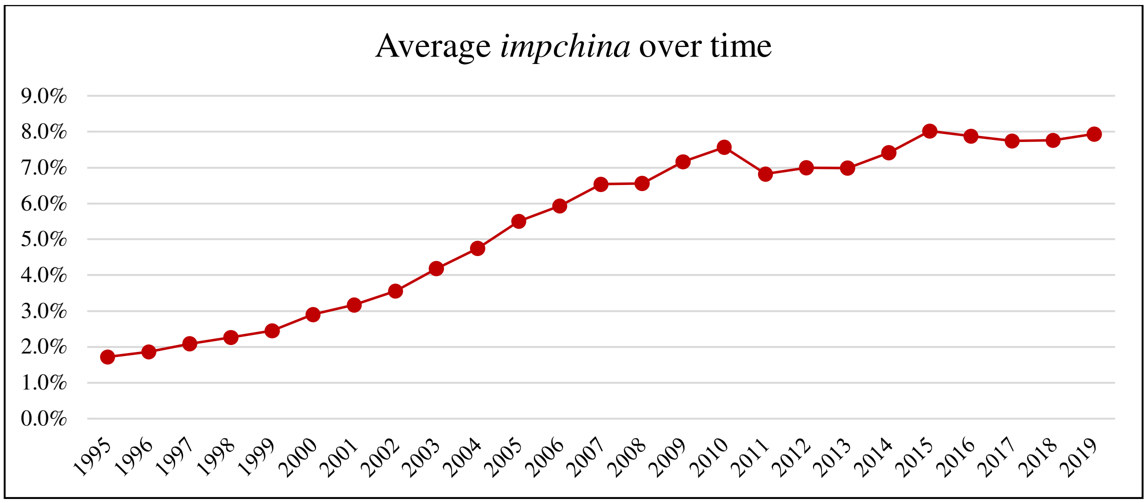


Figure 3: Graph of the average values of *impchina* per year.

From the graph above, we can already see that the share of goods imported from China by the countries of our sample has grown of almost 6% from year 1995 to year 2019 and the variation was always positive from a year to another, except for a few years where the value stayed stable (from 2012 to 2013) or decreased slightly. Possible explanations for such exceptions could be the starting point for further investigations for future research. From the graph it is also already evident that the (already positive) slope of the graph increased in the years following 2001, after China entered the WTO.

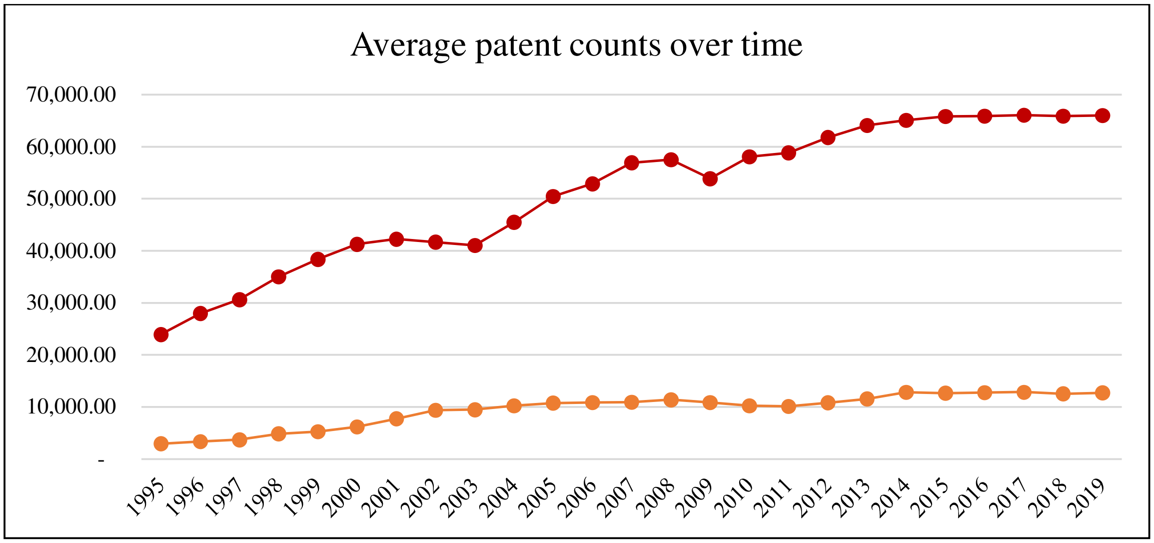


Figure 4: Graph of the average values of *pat* (red top line) and *tech* (orange bottom line) per year.

The trend of the total patent count is apparently positive as well (although any trends will be investigated in the next paragraph), with always positive yearly variations, except for the periods from 2001 to 2003 and from 2008 to 2009 (while this negative variation goes on until 2011 in the case of high-tech patents). From 2000 to 2001 the number of total imports decreases as well and we can’t exclude a lagged correlation between these two phenomena yet. The negative variation from 2008 to 2009 (to 2011 for the high-tech sector) could instead be - at least partially - caused by the financial crisis.

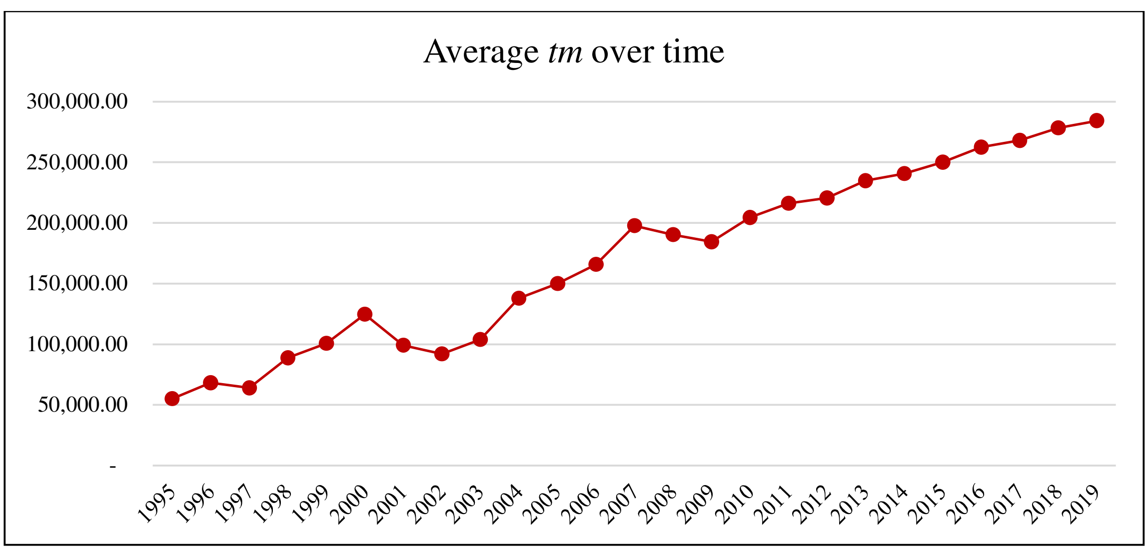


Figure 5: Graph of the average values of *tm* per year.

Trademark counts follow a similar path comparing to patents: the only negative variations are from 1996 to 1997 (slight), from 2000 to 2002 (much larger) and from 2007 to 2009 during the financial crisis.

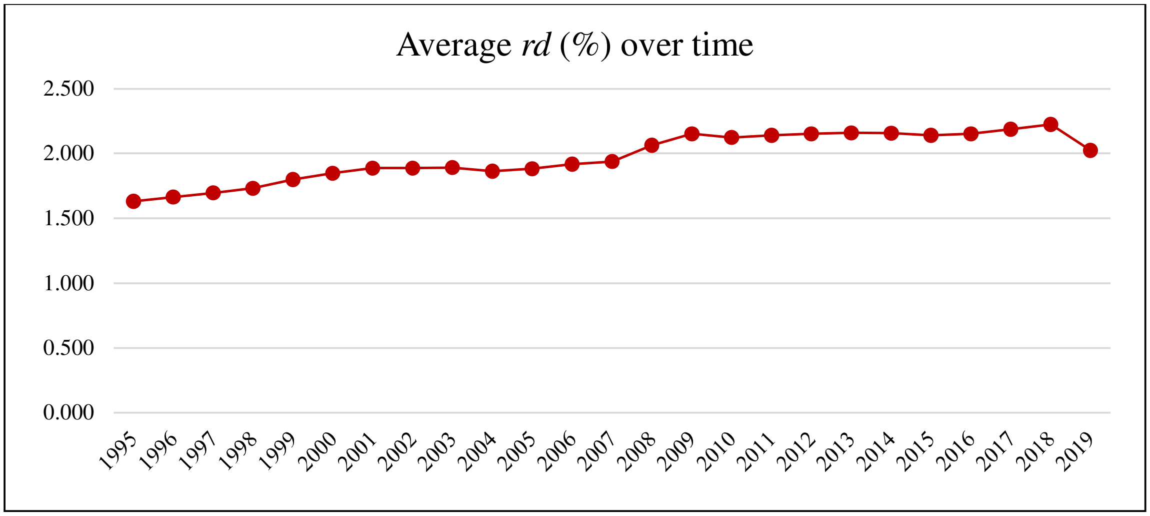


Figure 6: Graph of the average values (%) of *rd* per year.

The average percentage of R&D expenditure over GDP seems quite constant over time, but with always positive variations, except for a few slightly negative ones (the largest is just at the end of our period of analysis, from 2018 to 2019). Anyway, we will check for the presence of an actual trend in the next paragraph.

Here below, we report the graphs showing innovation outputs per million population.

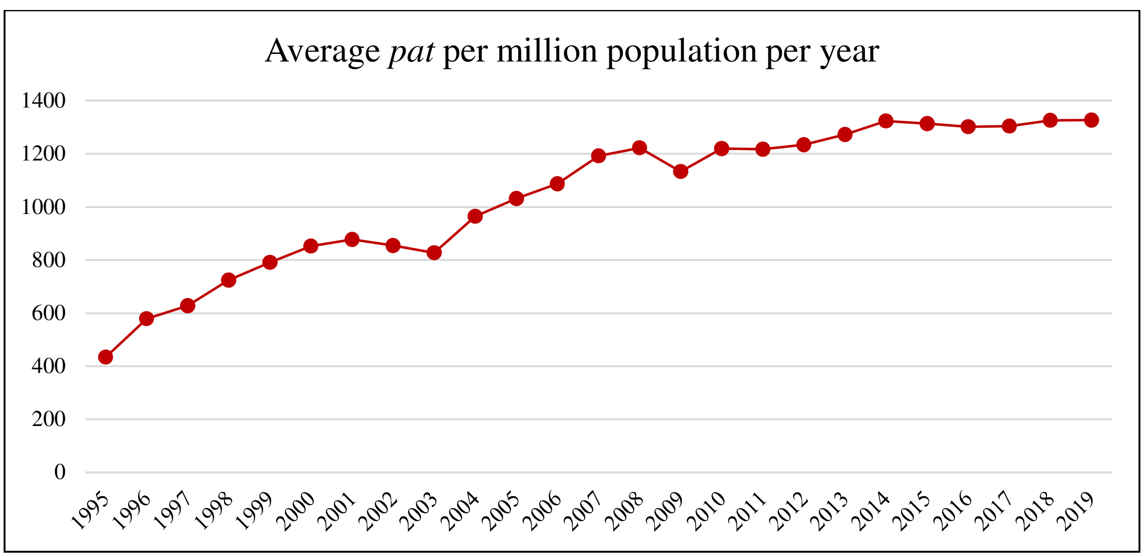


Figure 7: Graph of the average values of *pat* per million population per year.

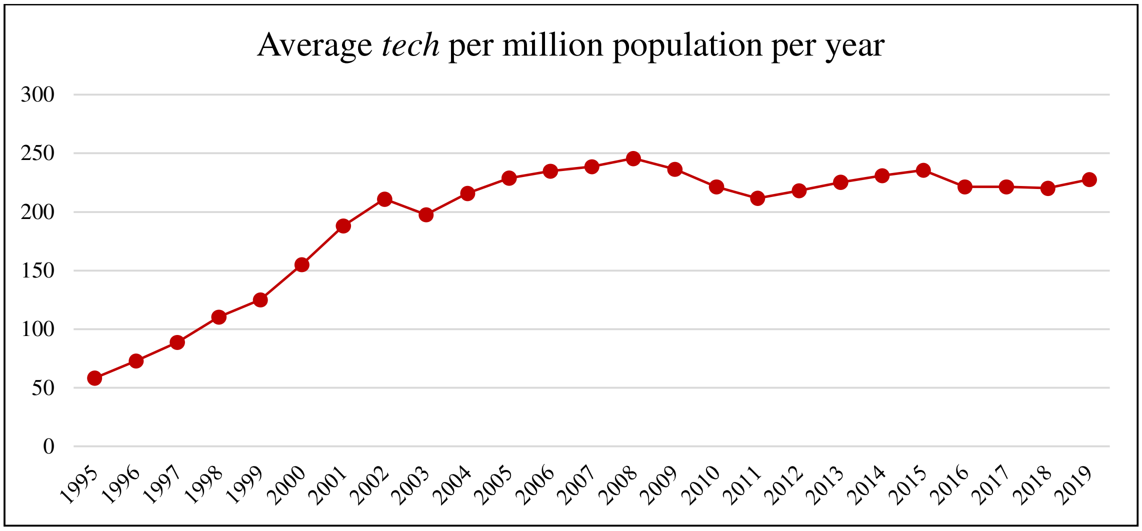


Figure 8: Graph of the average values of *tech* per million population per year.

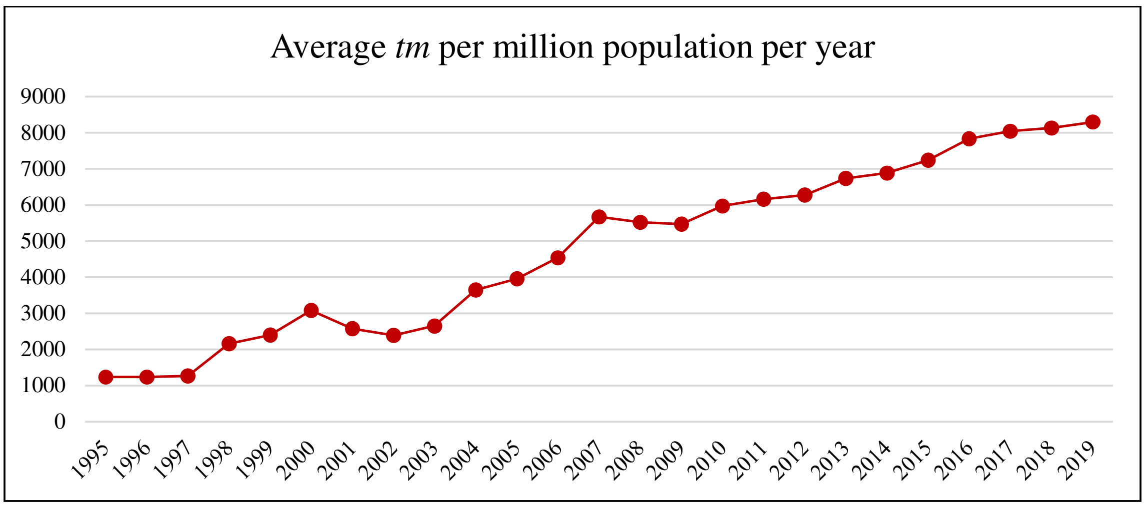


Figure 9: Graph of the average values of *tm* per million population per year.

Here below we also report the graphs[19] of the average values per country.

[15] Ibidem.

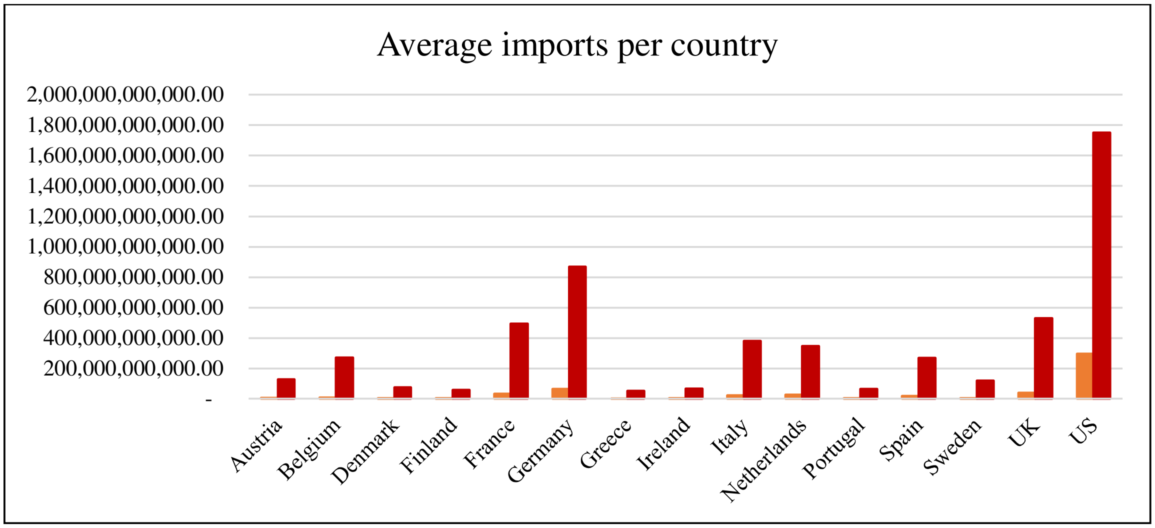


Figure 10: Graphs of the average values of *impchinavol* (shorter orange bars) and *impworld* (longer red bars) per country.

In terms of total imports from the whole world, the US and Germany are the first two countries (even though US value is twice the one of Germany). The other countries are all under 600 billion dollars of imports (taking into account that US import for almost 1800 billion dollars). The import volumes from China follow a similar pattern, even though the difference between the US and the other countries of the panel is much larger than the previous one. Such combination of positive and negative variations is also showed in the graph showing the proportion of import from China over the total imports from the world.

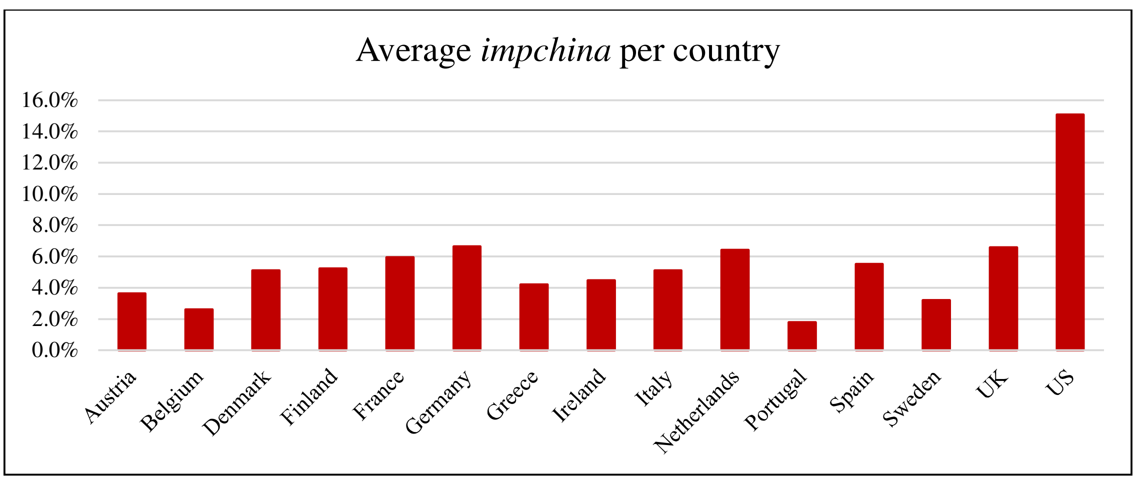


Figure 11: Graph of the average values of *impchina* per country.

The previous paths can also be summarized by the graph here above: except for a few exceptions, the values of the ratio do not vary much one from another and they are all between slightly under 4% and slightly above 6%. The most relevant outlier is represented by the US and this reflects the enormous difference from the other values of the import volumes from China, also with respect to such gap concerning the total amount of imports. The second highest value is still represented by Germany.

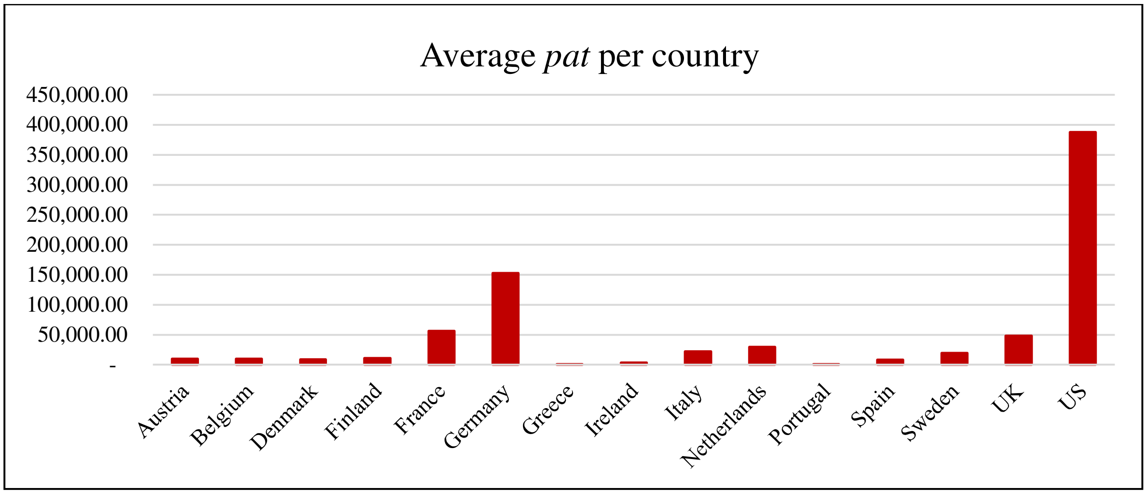


Figure 12: Graph of the average values of *pat* per country.

Just like for other previous variables, the average values of total patent counts do not differ much one-another, except for Germany and, most of all, the US.

Anyway, taking the same values normalizing them for populations, we find resulting ratios that differ much more from each other, and the US and Germany turn out to be, respectively, the fourth and the fifth highest values among the 15 ones, while Portugal, Greece, Spain, and Italy have the lowest amounts.

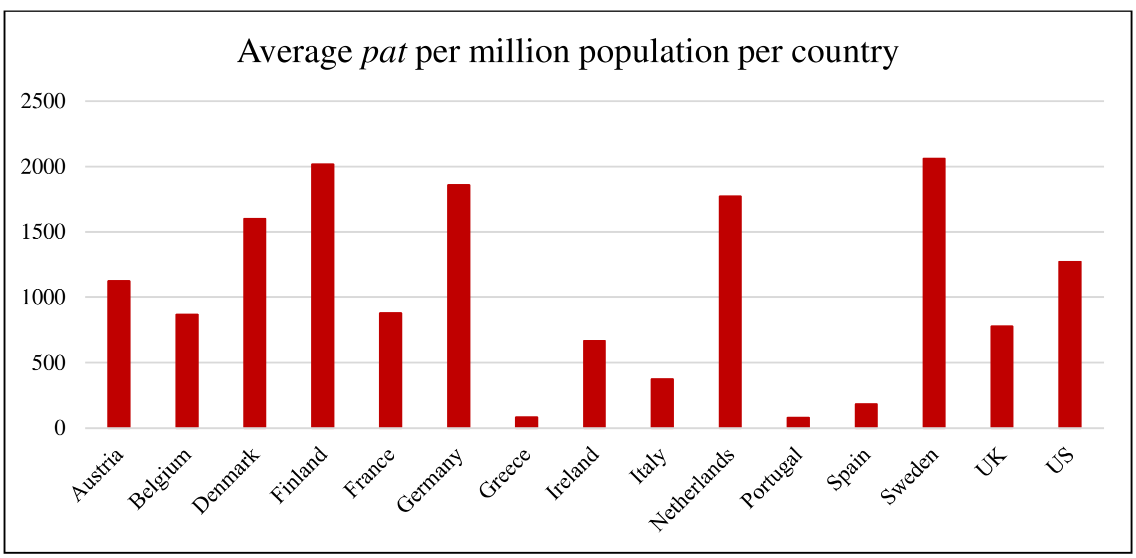


Figure 13: Graph of the average values of *pat* per million population per country.

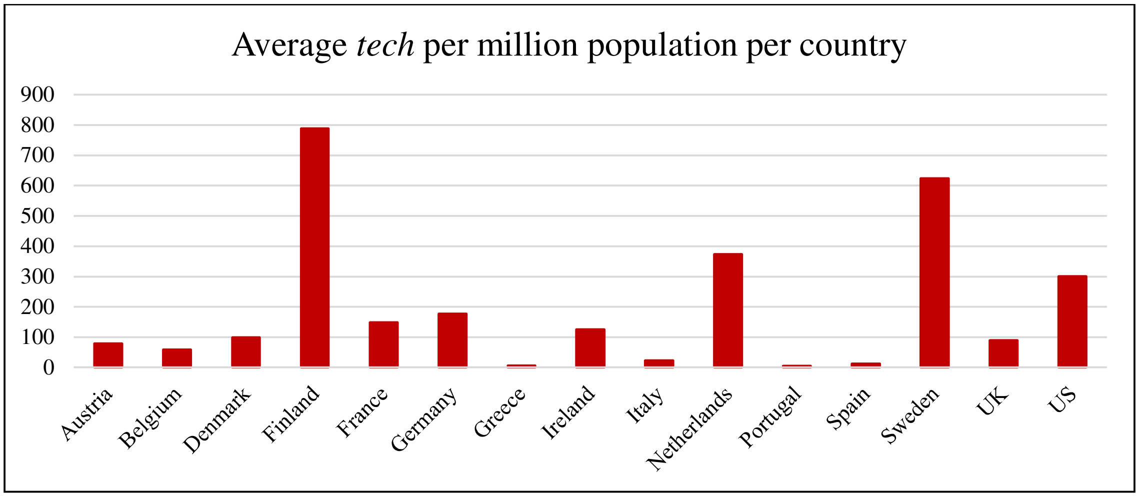


Figure 14: Graph of the average values of *tech* per million population per country.

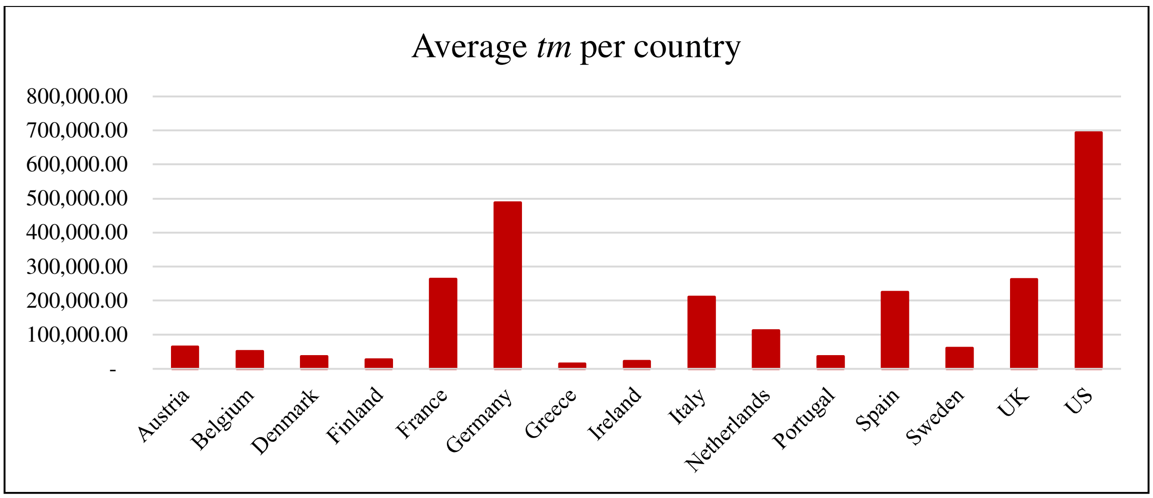


Figure 15: Graph of the average values of *tm* per country.

Just like in the case of the patent count, the US, Germany, and France show the highest values, while Greece, Ireland, Finland, and Denmark have the lowest. Nevertheless, with respect to patent counts, total trademark counts vary much more from each other.

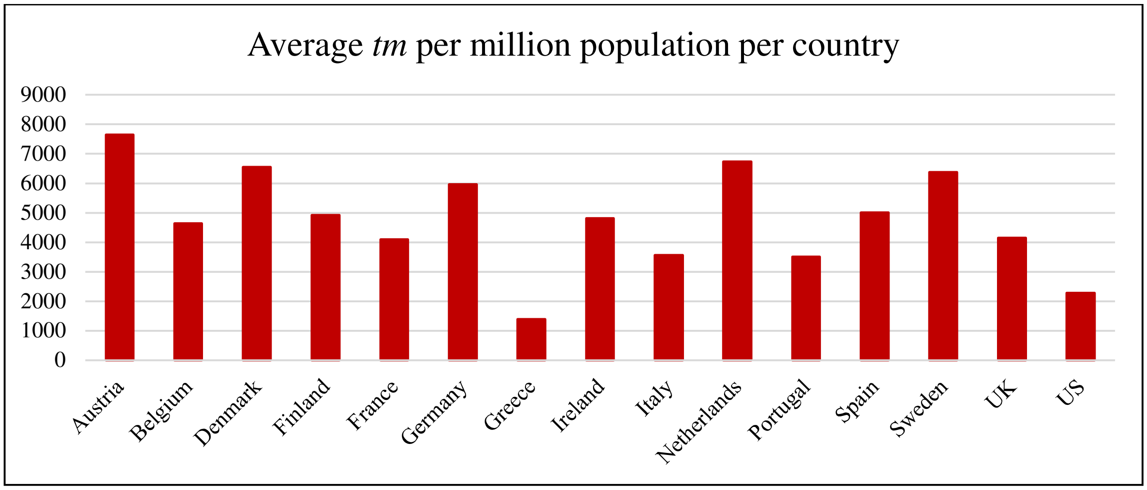


Figure 16: Graph of the average values of *tm* per million population per country.

Normalizing the previous counts for populations, the US turn out to have the second lowest ratio, after Greece, which is still one of the lowest also in the previous rankings we reported for IPR counts. On the other hand, Denmark, which had the fourth lowest trademark total count, has now the third one relatively to its population count, and the ratio is certainly not that low for Ireland, the second last in the total count, as well.

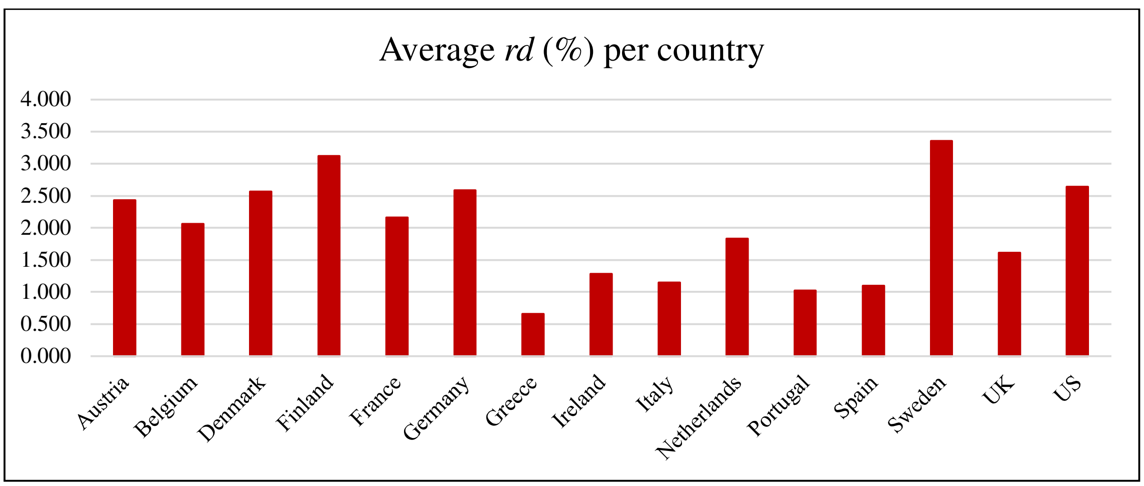


Figure 17: Graph of the average values (%) of *rd* per country.

To summarize the previous considerations, the US, Germany, the UK, the Netherlands, and France come out to be the countries with the highest average proportion of imports from China over imports from the whole world. The US, Germany and France also have the highest average number of total patents and of total trademarks. This result is clearly likely to be somehow affected by the dimensions of the countries, or at least by their population: if we look at the same indicators normalizing for population, the US and the UK show no such high values.

Nevertheless, the Netherlands are always among the first three countries for the three normalized indicators we are considering; Germany is always one of the first five.

We a report the main descriptive statistics of all our data[20]:

Table 5: Descriptive statistics.

Descriptive statistics	*impchina*	*rd* (%)	*stockpatpop*	*stocktechpop*	*stocktmpop*
Mean	0.054	1.973	0.0051	0.0010	0.022
Mode	-	-	-	-	-
Median	0.049	1.906	0.0042	0.0004	0.017
Standard Deviation	0.039	0.840	0.0044	0.0014	0.017
Variation Coefficient	0.715	0.424	0.8656	1.4224	0.771
Maximum	0.219	3.874	0.0156	0.0058	0.072
Minimum	0.006	0.290	0.00001	0.0000007	0.0005

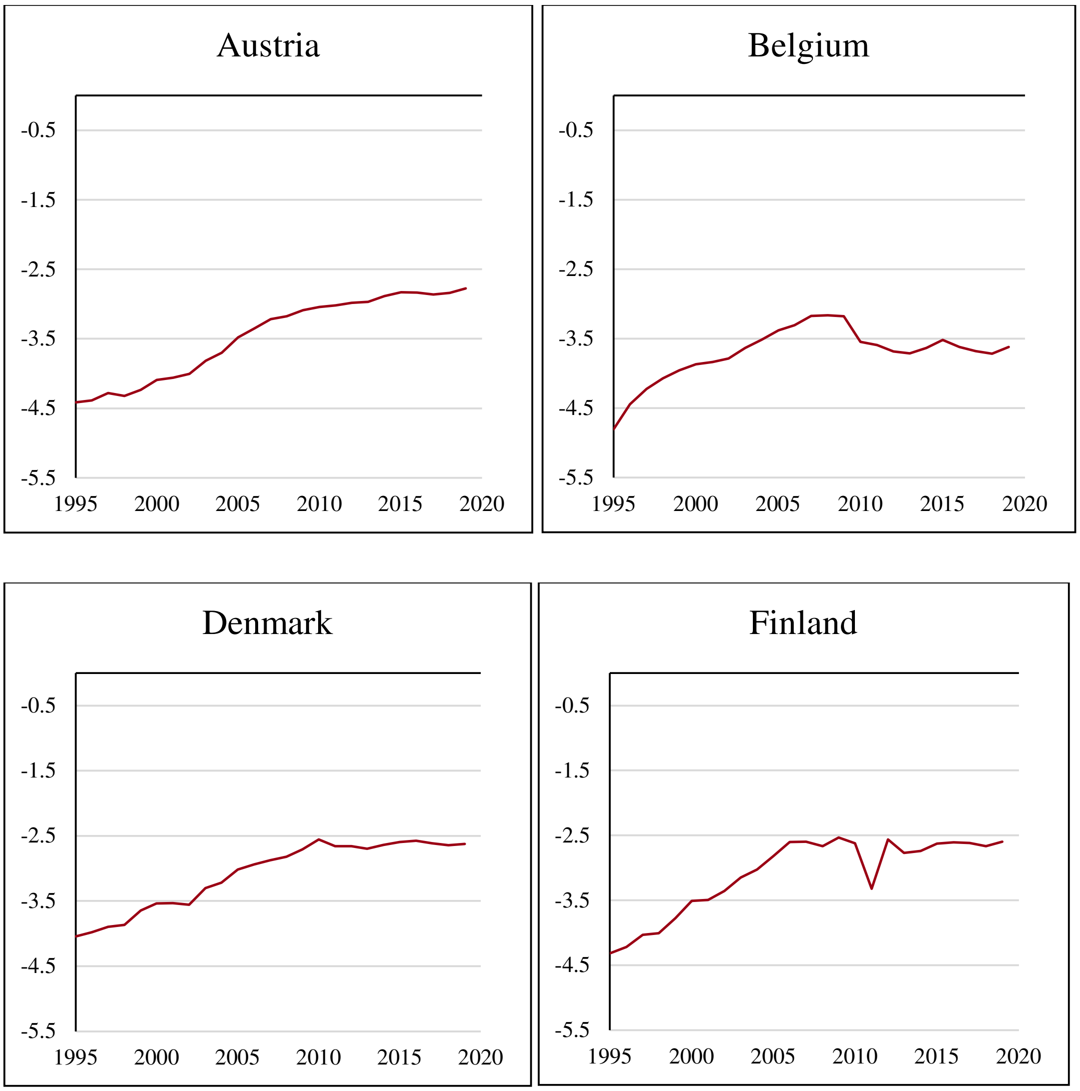
Table 6: Indexes *Voice_Acc, Pol_Stab, Gov_Eff, Reg_Q, R_Law, C_Corr, Inst_Q* - general descriptive statistics. We calculated *Inst_Q* as an average value of all the six indicators.

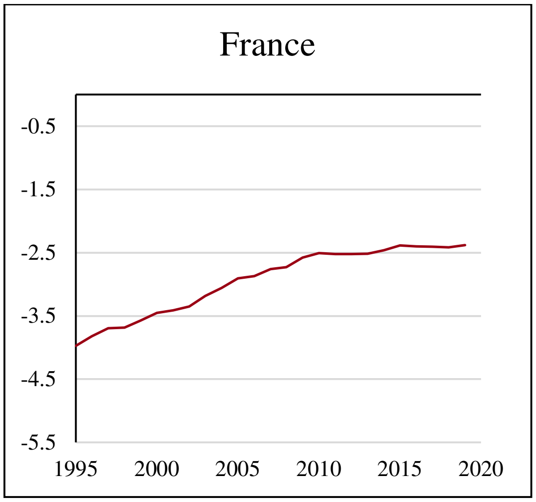
Descriptive statistics	*Voice_Acc*	*Pol_Stab*	*Gov_Eff*	*Reg_Q*	*R_Law*	*C_Corr*	*Inst_Q*
Mean	1.32	0.85	1.52	1.41	1.49	1.53	1.35
Mode	-	1.29	-	-	-	-	-
Median	1.34	0.92	1.63	1.51	1.61	1.59	1.43
Standard Deviation	0.21	0.46	0.48	0.39	0.44	0.64	0.39
Variation Coefficient	0.160	0.544	0.314	0.277	0.295	0.419	0.291
Maximum	1.80	1.76	2.35	2.10	2.13	2.47	1.97
Minimum	0.62	-0.47	0.16	0.15	0.07	-0.18	0.15

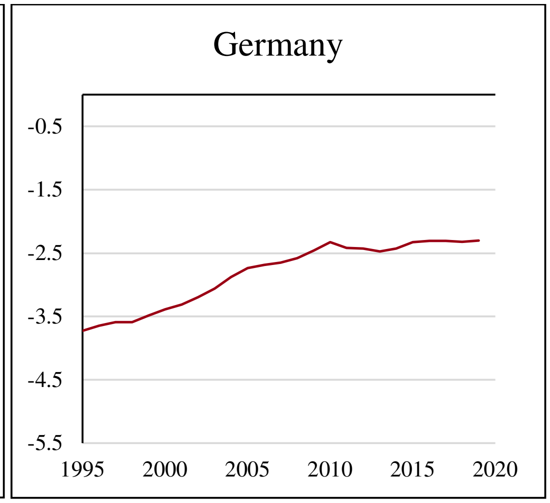
[20] All the descriptive statistics were calculated with Microsoft Excel; where the series has no mode, it will be replaced with a “-“ in the tables.

3.2.2 Empirical tests

Before starting our analysis, we report (in the next two figures) the panel graphs of the two main variables we focus on (already logarithmically transformed) *ln(impchina)* (where *impchina* is the ratio between the imports from China and the total imports) and *ln(stockpatpop)* visually reporting how such variables vary over time in the different countries.




France
-0.5
-1.5
-2.5
-3.5
-4.5
-5.5
1995
2000
2005
2010
2015
2020


Germany
-0.5
-1.5
-2.5
-3.5
-4.5
-5.5
1995
2000
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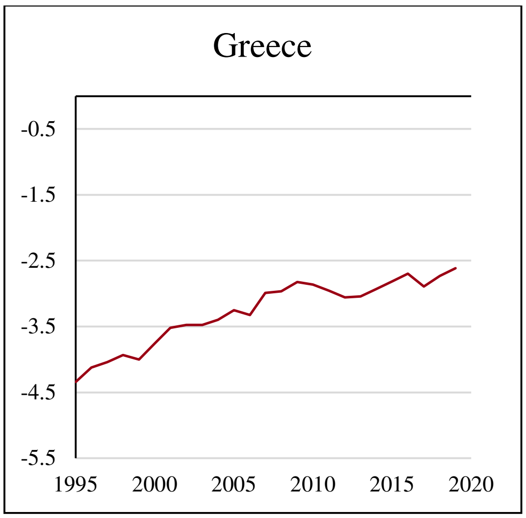
2015
2020


Greece
-0.5
-1.5
-2.5
-3.5
-4.5
-5.5
1995
2000
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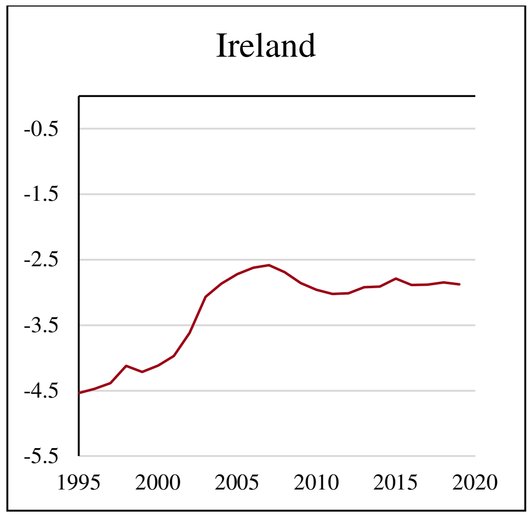
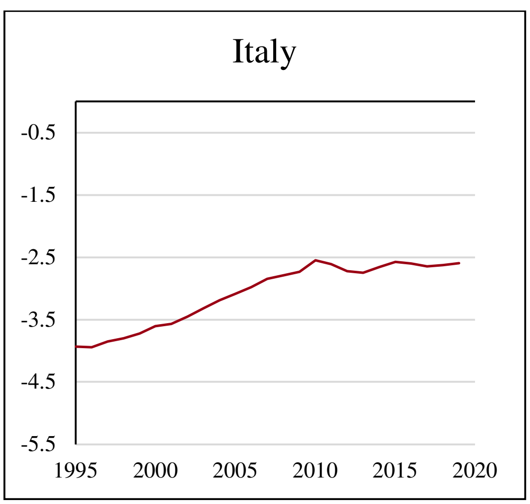
2020


Ireland
-0.5
-1.5
-2.5
-3.5
-4.5
-5.5
1995
2000
2005
2010
2015
2020


Italy
-0.5
-1.5
-2.5
-3.5
-4.5
-5.5
1995
2000
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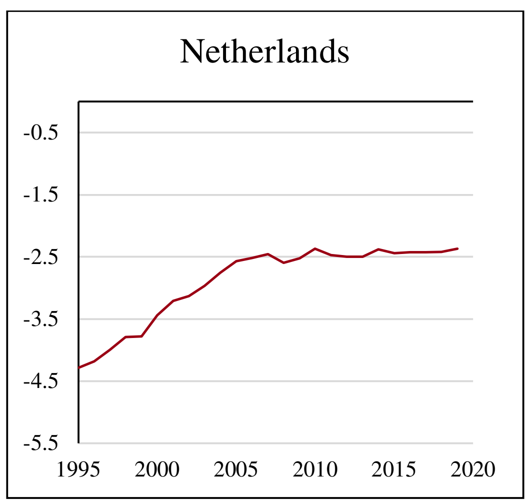
Netherlands
-0.5
-1.5
-2.5
-3.5
-4.5
-5.5
1995
2000
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2020

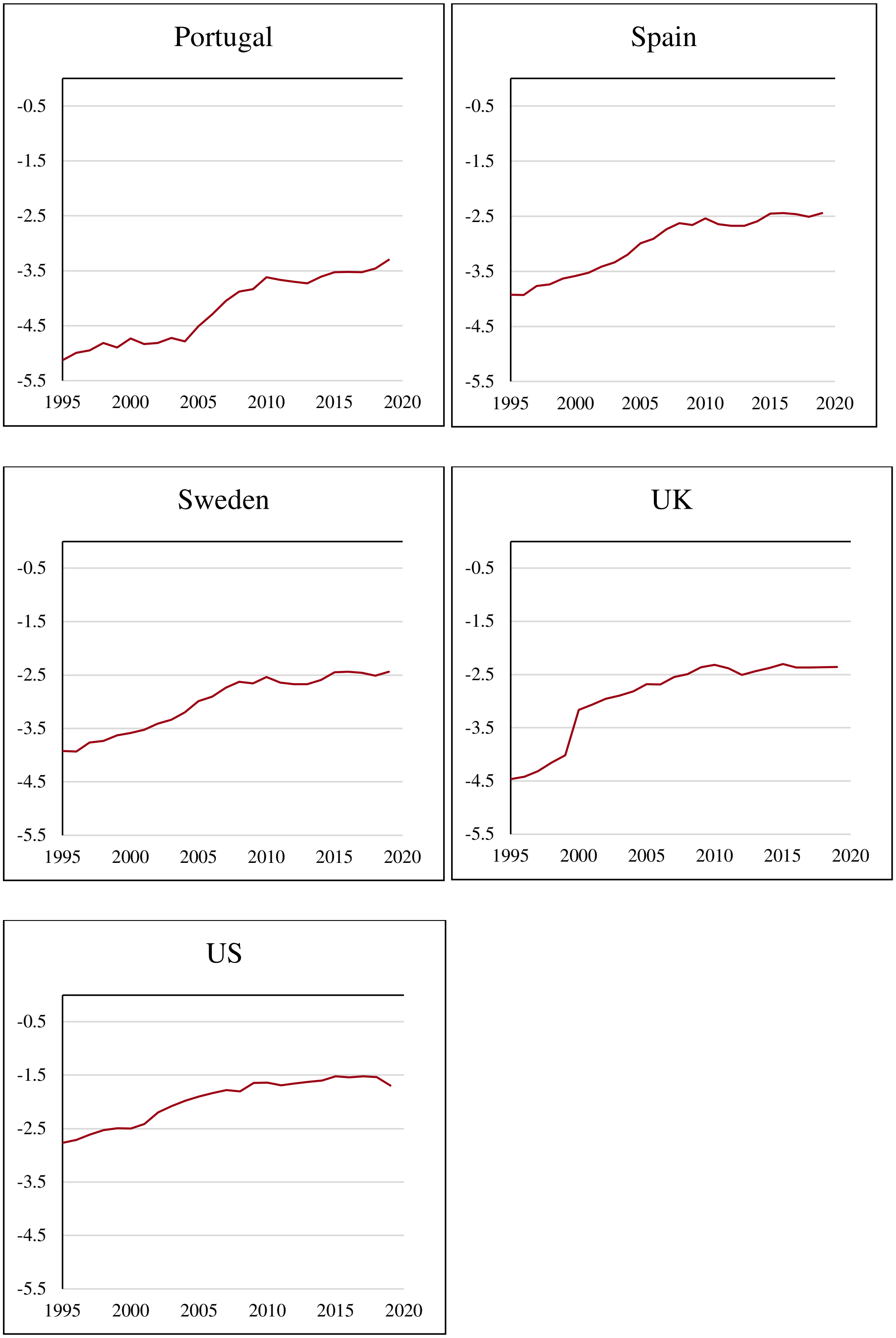
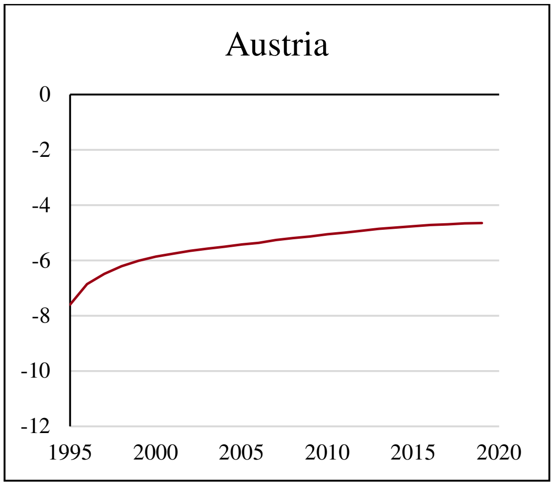
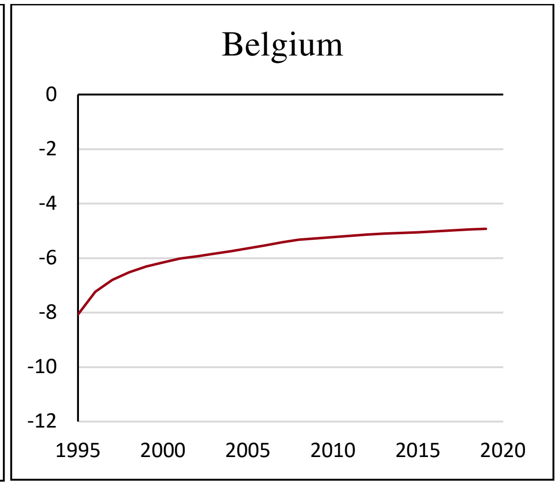
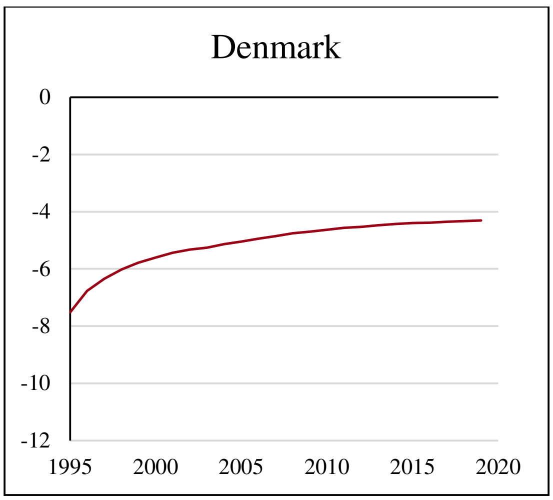


Figure 18: Panel graphs of the variable *ln(impchina)* for each country of the sample.


Austria
0
-2
-4
-6
-8
-10
-12
1995 2000 2005 2010 2015 2020


Belgium
0
-2
-4
-6
-8
-10
-12
1995 2000 2005 2010 2015 2020


Denmark
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-2
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-6
-8
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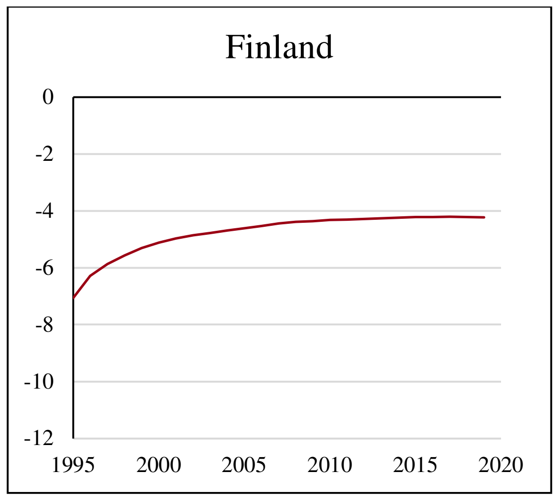
-12
1995 2000 2005 2010 2015 2020


Finland
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-2
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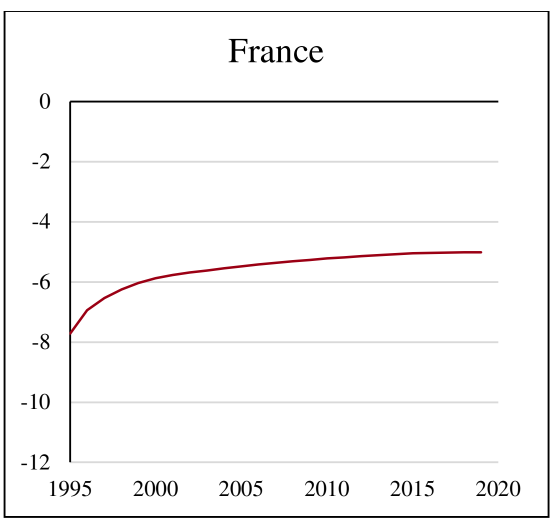
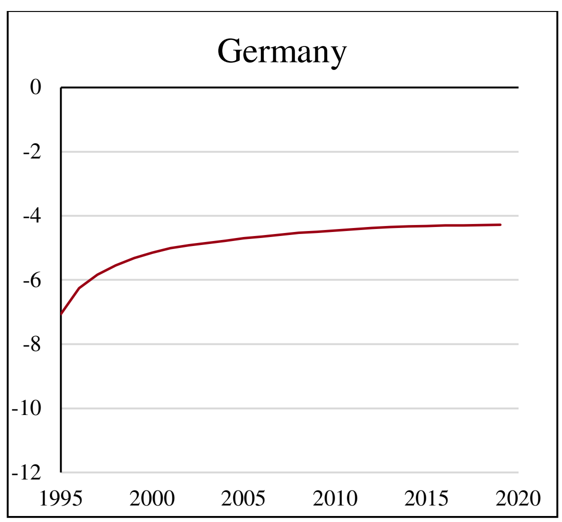
-8
-10
-12
1995 2000 2005 2010 2015 2020


France
0
-2
-4
-6
-8
-10
-12
1995 2000 2005 2010 2015 2020


Germany
0
-2
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-6
-8
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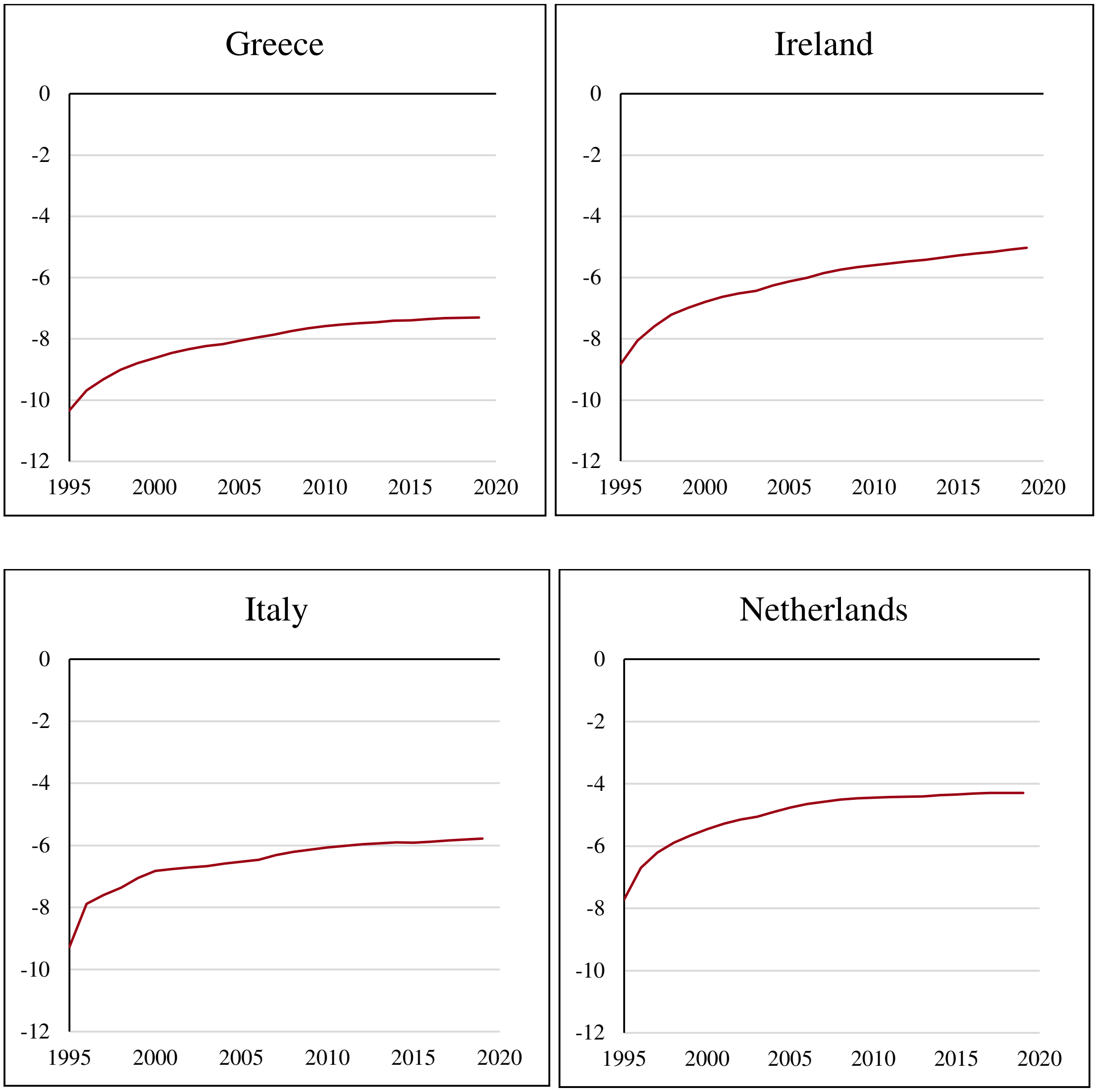
-12
1995 2000 2005 2010 2015 2020


Greece
Ireland
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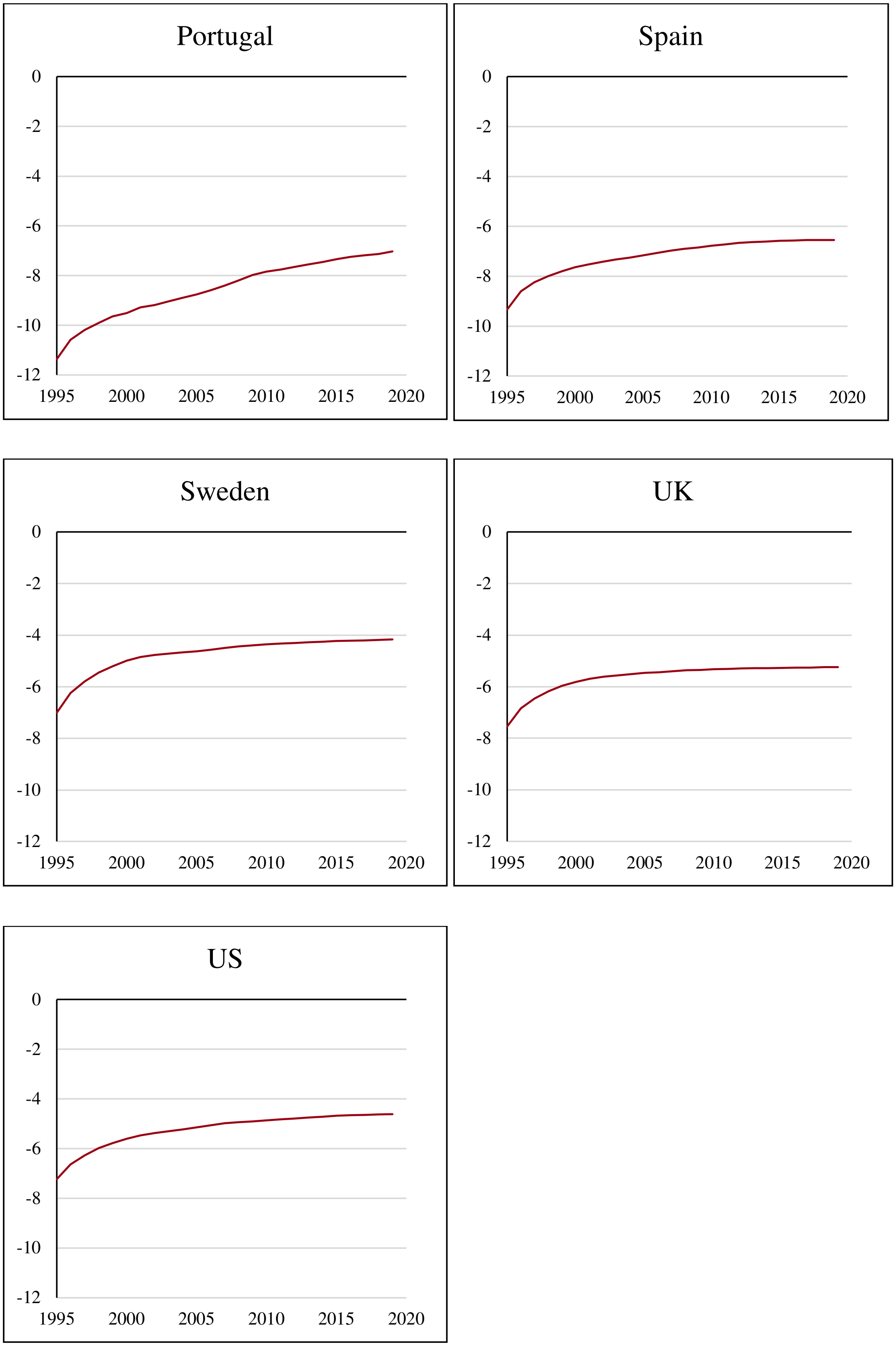

Figure 19: Panel graphs of the variable *ln(stockpatpop)* for each country of the sample.

To analyze the relationship between imports from China and innovation, we perform a number of empirical tests.

First, we check if our output variables (*ln(stockpatpop)*, *ln(stocktechpop)* and *ln(stocktmpop))*), our input variable (*ln(impchina)*), and our control variables (*Inst_Q*, *ln(rd)*, and *ln(nifdi)*) are stationary or not. From the graphs in the previous paragraph, it is reasonable to assume that most of the variables are characterized by a trend, or by a unit root, which would mean that they are non-stationary. We use the Pesaran (2007) panel unit root test. If they are non-stationary, we go on with our analysis by testing them for their panel cointegration, using the Westerlund (2007) cointegration test. If they are stationary, we do not test them any further. If, with the Westerlund (2007) cointegration test, they come out to have a common trend, then they are cointegrated, which means that their linear combination is stationary, and their relationship in the long run is not spurious. If instead they are not cointegrated, then any of their linear combinations is non-stationary, and the relationship with them can be spurious.

Cointegration has also three other properties. First, the model is robust to other omitted stationary variables: if a stationary variable is omitted from the regression, it is still not part of the error term, so the residuals remain stationary. The second property is that the cointegrated variables are still cointegrated even when adding more variables to the regression. Third, the errors remain stationary for the cointegrated variables (Herzer and Donaubauer, 2018; Stock, 1987).

Next, we proceed investigating the long-run relationship of *ln(stockpatpop)* with the independent variable *ln(impchina)*, also including those control variables which are cointegrated with the output variable *ln(stockpatpop)*, using the Kao and Chang (2000) Dynamic Ordinary Least Squares (DOLS) method, which is also robust to endogeneity.

We also divide the countries into four groups according to their geographical position, and repeat the DOLS estimates for each region, to check for the robustness of the results and see how they vary across the four different areas.

Lastly, we test for Granger long- and short-run causality by using the pooled mean-group estimator (PMG) and the consequent error-correction model (ECM). Starting from two equations (which differ from each other just for having explanatory and dependent variable inverted), we check for short-run causality by looking at the coefficient of their regressor; then, we test for long-run causality by looking at their EC (error-correction) term (the error-correcting-speed-of-adjustment term to the long-run equilibrium).

The starting baseline equation is:

$$\ln stockpatpop_{it} = \beta \ln impchina_{it} + \mu_i + \lambda_t + \varepsilon_{it} \qquad (1)$$

where β is the elasticity of *stockpatpop* with respect to *impchina*, μ_i is the vector of country-specific fixed effects, and λ_t is the vector of year-specific fixed effects, included to control for macroeconomic trends. Finally, ε_{it} is the stochastic error term.

3.2.2.1 Unit root test

Pesaran's (2007) panel unit root test is called cross-sectional Im, Pesaran and Shin (CIPS) test[21]. Its null hypothesis is that the variable has a unit root. In order to reduce heteroskedasticity problems, we test most of our variables applying a logarithmic transformation (*ln*), then we test the first differences. If the test does not reject the null hypothesis for the variables in levels but rejects it when such variables are put in first differences, then they are integrated of order 1, i.e., they are non-stationary.

We set the lags of the variables according to the lags criterion decision Portmandeau (Q) test for white noise[22].

Results are showed here below.

Table 7: Pesaran (2007) unit root test – dependent, explanatory and control variables.

Pesaran (2007) unit root test – dependent variables.

	ln(stockpatpop)	*ln(stocktechpop)*	*ln(stocktmpop)*
CIPS	-2.584	-2.629	-2.592
	Δln(stockpatpop)	*Δln(stocktechpop)*	*Δln(stocktmpop)*
CIPS	-3.641***	-3.104***	-4.212***

Pesaran (2007) unit root test – explanatory and control variables.

	ln(impchina)	*Inst_Q*	*ln(rd)*	*ln(nifdi)*
CIPS	-2.685	-1.698	-1.487	-3.729***
	Δln(impchina)	*ΔInst_Q*	*Δln(rd)*	*Δln(nifdi)*
CIPS	-4.449***	-4.301***	-4.016***	-6.253***

Note: all relevant at 10%, 5%, and 1% values are, respectively: -2.6, -2.7, and -2.89 without first-differencing, and -2.59, -2.69, and -2.88 when applying the first difference. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

[21] Stata code: `xtcips`.

[22] Maximum number of lags was set to 5.

The test is for all first-differenced variables significant at 1% level, and also significant at 1% level for the variable *ln(nifdi)* without differencing it. The other ones are not significant at all. Thus, the variables *ln(impchina)*, *ln(stockpatpop)*, *ln(stocktechpop)*, *ln(stocktmpop)*, and *Inst_Q* have all a unit root and are non-stationary, meaning that they follow a trend.
Given such results, our next step is proceeding with the analysis of the non-stationary variables, to check whether such trend is common or if it is different for each different variable.

3.2.2.2 Cointegration test

The next step in our empirical analysis is investigating whether *ln(impchina)* and *ln(stockpatpop)* (and *ln(stocktechpop)* and *ln(stocktmpop)*) are cointegrated. To do so, we use the Westerlund (2007) cointegration test[23], which consists of four statistics (G_τ, G_α, P_τ, P_α) and is based on the ECM (Error Correction Model). The G_τ and G_α statistics (according to Westerlund, 2007) test the null hypothesis of absence of cointegration against the alternative that implies cointegration for at least one cross-sectional unit, whereas the panel statistics P_τ and P_α test the null hypothesis of absence of cointegration against the alternative that the whole panel is cointegrated (Herzer and Donaubauer, 2018). In doing so, due to the relatively limited number of years available, we use a one-year lag.

One issue is the potential cross-sectional dependence of the data because of omitted common factors. "Such factors may be a combination of "strong" factors representing global shocks and "weak" factors representing spillovers" (Herzer and Donaubauer, 2018, p. 322) between neighboring countries. These unobservable factors can lead to a violation of the common assumption of independence across units, which is strictly required in order to apply the standard panel unit root tests, where the average statistic of units should converge to the Normal distribution, so to meet the requirements of the central limit theorem in the elaboration of the unit-root statistic and of the estimators and tests that are an average of individual relationships (Burdisso and Sangiacomo, 2016). In order to control for cross-sectional dependence, we use the bootstrap approach with 500 replications, as suggested by Westerlund (2007).

Results are showed here below.

Table 8: Westerlund (2007) cointegration test - *ln(stockpatpop)*, *ln(impchina)*.

Statistic	Value	Robust p-value

[23] Stata code: `xtwest`.

G_τ	-3.926	0.002***
G_α	-47.199	0.000***
P_τ	-13.013	0.006***
P_α	-35.617	0.000***

Note: bootstrapped *p*-values based on 500 replications. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table 9: Westerlund (2007) cointegration test - *ln(stocktechpop)*, *ln(impchina)*.

Statistic	Value	Robust *p*-value
G_τ	-2.555	0.160
G_α	-19.230	0.000***
P_τ	-7.083	0.650
P_α	-13.066	0.002***

Note: bootstrapped *p*-values based on 500 replications. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table 10: Westerlund (2007) cointegration test - *ln(stocktmpop)*, *ln(impchina)*.

Statistic	Value	Robust *p*-value
G_τ	-2.649	0.180
G_α	-12.182	0.028**
P_τ	-9.489	0.186
P_α	-10.105	0.068*

Note: bootstrapped *p*-values based on 500 replications. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

When testing for cointegration between *ln(stockpatpop)* and *ln(impchina)* we find that all the four statistics are simultaneously significant at level 1%, therefore, we know that the two variables are cointegrated not only in at least one country, but across all the countries of the panel. The test concerning *ln(stocktechpop)* and *ln(impchina)* results in 1%-significant G_α and P_α statistics, but in non-significant G_τ and P_τ statistics. Thus, cointegration between these two variables exists, but it is less robust. Lastly, when testing for cointegration of the imports from China with the trademarks stock (*ln(stocktmpop)*), results are not much robust and significant as well, but some cointegration still exists: statistic G_α is significant at 5% level and P_α is only significant at 10% level. For this reason, we only focus on the cointegration between import competition and patents, where the Westerlund (2007) statistics are the most significant.

3.2.2.3 Testing the long-run relationship between patents and imports from China

In this step, we investigate the long-run cointegration relationship of *ln(stockpatpop)* with the independent variable *ln(impchina)* using the DOLS approach developed by Kao and Chiang (2000)[24].

The equation of the DOLS analysis is:

$$\ln stockpatpop_{it} = \beta \ln impchina_{it} + \mu_i + \lambda_t + \sum_{j=-p}^{p} \gamma_{ij} \Delta \ln impchina_{it} + u_{it} \qquad (2)$$

where p represents the number of lags, that we set equal to 1, and where μ_i is included as country-specific fixed effect and λ_t is included as year-specific fixed effect.

After DOLS-testing for the long-run relationship between *ln(stockpatpop)* and *ln(impchina)*, we also add those control variables which have a unit root: *Inst_Q* and *ln(rd)*.

Then, we also take each variable subtracting its cross-sectional mean, thus ending up analyzing the demeaned data, in order to control for any other unobserved common factors and further reduce any possible cross-sectional dependence.

Results are showed in the following table:

Table 11: DOLS estimates - *Kao and Chiang (2000) pooled DOLS estimator.*

Dep. var.: *ln(stockpatpop)*	DOLS (1)	DOLS (2)	DOLS (3)
No. observations	330	330	330
R^2	0.837	0.807	0.841
ln(impchina)	1.063***	0.679***	0.888***
Std. error	0.070	0.067	0.067
Inst_Q		0.686***	-0.887***
Std. error		0.259	0.259
ln(rd)		1.585***	0.038
Std. error		0.182	0.182
Demeaned data	No	No	Yes

Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Our results in column (1) show that there is a strong positive long-run relationship between *ln(impchina)* and *ln(stockpatpop)* and that it is significant at 1% level. Column (2) shows that such strong relationship holds also when controlling for the quality of the institutions and the R&D intensity of countries. In column (3) results are reported when analyzing the

[24] Stata code: `xtdolshm`.

relationship with the two control variables, but with demeaned data. The 1%-statistically-significant coefficients indicate that the relationship is also robust to cross-sectional dependence.

3.2.2.4 Robustness of the results to different geographical contexts

Now we check if the results of the DOLS analysis are also robust to different geographical contexts. We group the countries of our sample into different regions according to their geographical position and we re-estimate the DOLS equation for the different geographical areas. In this way, we can check whether the DOLS results we previously reported are homogeneous across the whole OECD sample or depend on the specific geographical context. In this analysis, we also include the quality of institutions *Inst_Q*.

Table 12: Geographical division of the countries of the sample.

Geographical regions	Countries
Northern Europe	Denmark
	Finland
	Ireland
	Sweden
	UK
Western Europe	Austria
	Belgium
	France
	Germany
	Netherlands
Southern Europe	Greece
	Italy
	Portugal
	Spain
US	US

Here below, we show the results of the regional DOLS analysis.

Table 13: Region-specific DOLS estimates.

Dep. var.: *ln(stockpatpop)*	*ln(impchina)*	*Inst_Q*
Northern Europe	0.689***	2.848***
	(0.107)	(0.621)
Western Europe	0.819***	0.957
	(0.132)	(0.681)
Southern Europe	1.441***	0.432
	(0.147)	(0.387)
US	1.667***	1.701***
	(0.138)	(0.369)

Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Results show that, also when focusing on specific geographical areas, the relationship between *ln(stockpatpop)* and *ln(impchina)* remains 1% statistically significant. The relationship with *Inst_Q* is only significant for countries in Northern Europe and for the US.

Since we know from the Westerlund (2007) test that imports from China are also somehow cointegrated with the high-tech patents, we test the relationship between the two variables in the different regional context.

We show the results here below.

Dep. var.: *ln(stocktechpop)*	*ln(impchina)*	*Inst_Q*
Northern Europe	0.685***	3.600***
	(0.120)	(0.696)
Western Europe	1.586***	1.128
	(0.163)	(0.839)
Southern Europe	1.531***	0.247
	(0.183)	(0.482)
US	1.946***	0.983**
	(0.171)	(0.458)

Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Also when focusing on high-tech patents, the relationship with *ln(impchina)* is 1% significant for all the geographical areas. The relationship with *Inst_Q*, like for the total patent count, is only significant in Northern Europe (1% level) and in the US (5% level).

3.2.2.5 Long-run and short-run causality

We now test our main variables for long-run causality, which may be actually from *ln(impchina)* to *ln(stockpatpop)*, from *ln(stockpatpop)* to *ln(impchina)* or in both directions. Although the significant cointegration test suggests that there must be some Granger causality in at least one of the two directions[25], it does neither tell us the direction of such a causality nor whether such causality is in the short or in the long run. To test for this, we employ a panel vector error correction model (PVECM) which uses the long-run cointegration regression DOLS coefficient to calculate the lagged error-correction (EC) term.

Specifically, we use the Pesaran, Shin and Smith pooled mean-group (PMG) estimator (1997, 1999)[26]. The starting point is the following dynamic panel specification:

$$lnstockpatpop_{it} = \sum_{j=1}^{p} \lambda_{ij} \Delta lnstockpatpop_{it-j} + \sum_{j=0}^{q} \gamma_{ij} \Delta lnimpchina_{it-j} + \epsilon_{it} \qquad (3)$$

where i stands for the country, t the year, γ is the coefficient of our explanatory variable *ln(impchina)*, λ is the coefficient of the lagged dependent variable, ε is the stochastic error term, and p and q are set equal to 1.

We already know that both *ln(impchina)* and *ln(stockpatpop)* are non-stationary and cointegrated, thus we can construct an error-correction model where their short-run dynamics are affected by the deviation from the long-run equilibrium. The EC term is basically the error-correcting-speed-of-adjustment term to the long-run equilibrium: if such term is equal to zero, then there is no long-run relationship between the two variables. If instead the coefficient of the lagged EC is significantly different from zero, and negative, then those two variables are characterized by a return to their long-run equilibrium and by a causal relationship.

The PMG estimator estimates the ECM, which consists of country-specific intercepts (the fixed effect), short-run coefficients and error terms, while the estimated long-run coefficient (the EC term) is the same across panels. To estimate the parameters, the model uses the maximum likelihood estimation (MLE).

To assess the long-run causality between the two variables, we start with estimating two equations: the first one (4) with *Δln(stockpatpop)* as dependent variable and *Δln(impchina)* as the main explanatory variable, the second one (5) with *Δln(impchina)* as dependent variable and *Δln(stockpatpop)* as the main explanatory variable. Our equations also include the intercept and the EC term. Next, we look at the estimated coefficient of the lagged EC terms in each equation (due to the limited number of years, we set *p* equal to 1 in both equations): if it is not

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[25] To deepen the Granger Representation Theorem, see: Granger, 1988.
[26] Stata code: `xtpmg`. The PMG estimator was proposed by Pesaran, Shin, and Smith, and allows the intercepts of a model, the short-run coefficients, and the error variances to differ freely across groups, but constrains the long-run coefficients to be the same across such panels (Pesaran *et al.*, 1999).

statistically different from zero in both equations, the explanatory variable is weakly exogenous and there is no long-run Granger causality between the variables. On the contrary, if it is statistically different from zero in both the equations, the long-run causality is mutual, and both the variables affect each other. Otherwise, one of the two affects the other but not vice versa, if the EC term is statistically significant only in one of the two equations.

Here we report the estimated equations:

$$\Delta \ln stockpatpop_{it} = \sum_{j=-p}^{p} \lambda_{1ij} \Delta \ln impchina_{it-j} + \gamma_{1i} + \sum_{j=-p}^{p} \mu_1 EC_{1t-j} + \varepsilon_{1it} \qquad (4)$$

$$\Delta \ln impchina_{it} = \sum_{j=-p}^{p} \lambda_{2ij} \Delta \ln stockpatpop_{it-j} + \gamma_{2i} + \sum_{j=-p}^{p} \mu_2 EC_{2t-j} + \varepsilon_{2it} \qquad (5).$$

We also check for short-run causality by focusing on the estimated coefficient of the lagged differenced explanatory variable in each equation: if this is not significantly different from zero, then there is no short-run Granger causality on the dependent variable.

Lastly, we perform another test, to check for strong exogeneity of the variables in our two equations. The null hypothesis of the test is that of strong exogeneity, and, in order for the explanatory variable to Granger cause the dependent one, the estimated coefficients of both such lagged differenced explanatory variable and the lagged EC term need to be jointly significantly different from zero. Otherwise, in the presence of strong exogeneity (if the two estimated coefficients are not jointly significant), the dependent variable cannot be Granger caused by the regressor, neither in the short nor in the long run (Herzer and Donaubauer, 2018).

Here below, we show all our results.

Table 14: PVECM estimates.

	(1)	(2)
Dep. var.	*Δln(stockpatpop)*	*Δln(impchina)*
Δln(impchina)	0.535***	
	(0.015)	
Δln(stockpatpop)		0.703***
		(0.058)
EC	-0.339***	-0.285***
	(0.030)	(0.045)
No. observations	360	360
No. countries	15	15

Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table 15: Short-run and long-run causality tests.

	Coefficients	*p*-values

Dep. var.: *Δln(stockpatpop)*		
Weak exogeneity test (long-run causality)		
Coeff. EC=0	127.22***	0.0000
Short-run Granger causality test		
Coeff. *Δln(impchina)*=0	13.01***	0.0003
Strong exogeneity test		
Coeff. EC=coeff. *Δln(impchina)* =0	129.96***	0.0000

Dep. var.: *Δln(impchina)*		
Weak exogeneity test (long-run causality)		
Coeff EC=0	39.75***	0.0000
Short-run Granger causality test		
Coeff. *Δln(stockpatpop)*=0	0.42	0.5163
Strong exogeneity test		
Coeff. EC=coeff. *Δln(stockpatpop)*=0	42.57***	0.0000

Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

First, we look at the parameters of the two equations to check for long and short-run Granger causality in the ECM. In both cases, the EC term is statistically different from zero (with a 1% level of significancy): this means that the causal relationship is mutual in the long run. The coefficient of the main regressor (*Δln(impchina)* in the first equation and *Δln(stockpatpop)* in the second one) is 1% significantly different from zero in the first equation and instead not significant in the second one. Thus, in the short run, imports from China Granger cause the variation in the stock of patents per population, but not vice versa: the causal relationship is in one direction only.

The results are confirmed in the last table, where we show the results of the direct test for the weak and strong exogeneity of the two variables and for short-run Granger causality. In both cases (the first with one dependent variable and the second with the other one), the test for the EC term is significant, indicating a long-run causality in both directions. The test for short-run causality is instead significant (meaning that the coefficient of the lagged differenced explanatory variable is statistically different from zero) only in the first case, confirming that it is only the import-from-China variable causing the variations in the stock patent level in the short run, and not vice versa. Both these results are confirmed by the significance (1%) of the strong exogeneity test, indicating absence of exogeneity.

3.3 Discussion of the results

In our research, we performed a series of tests, finding significant and robust results. We believe that such findings are also quite reliable, since, not only they all result in high R^2, but they are also generated by tests which included more than one important control variable. In addition to the year-specific and country-specific fixed effects, we considered the quality of institutions of the different countries and their R&D expenditure, but we also included population counts and GDP, incorporating them in the calculation of the other previously mentioned variables.

In this paragraph, we will better discuss our results. Step by step, we will cover the discussion of the results of all the tests we performed. We will start with the discussion of what we got from the unit-root and cointegration tests, proceeding with the DOLS analyses, both general and region-specific, and the comparisons with some of the past findings we mentioned in the literature review, and concluding first with the discussion of the short-run and then of the long-run-causal relationships we found in our final tests.

3.3.1 Trends and cointegration

The significance of the unit root tests shows that all the variables we tested (the independent variable *ln(impchina)*, the dependent variables *ln(stockpatpop)*, *ln(stocktechpop)*, and *ln(stocktmpop)*, and the control variables *Inst_Q*, *ln(rd)*, and *ln(nifdi)*) follow a trend, except for *ln(nifdi)*. Such trends were already visible in the graphs of the average values of the imports and of the flow of each type of IPR per year in paragraph 3.2.1.

Next, we tested for cointegration between the main regressor (*ln(impchina)*) and, respectively, *ln(stockpatpop)*, *ln(stocktechpop)*, and *ln(stocktmpop)*, getting significant results, except for the cointegration with *ln(stocktmpop)*: the imports from China share a common trend with the stock of patents and of high-tech patents in the countries of our sample, which we think, by the way, it is sufficiently large to allow a potentially reliable analysis.

3.3.2 DOLS analyses and comparisons with past findings

In the DOLS analysis, we found 1%-significant results of the very strong relationship between *ln(stockpatpop)* and *ln(impchina)*. Such coefficient in a log-log model means that, for example, if the value of the imports from China increases of 1%, then the stock of patents increases of 1.063%, since the resulting coefficient is equal to 1.063.

The relationship is also relevant if we control for R&D expenditure (*ln(rd)*) and for the quality of institutions (*Inst_Q*). In both cases the R^2 is quite high, indicating the good fit of our models for the phenomenon. In the second case, the relationship with the imports is slightly weaker, although it remains still relevant, and the coefficient is very similar to that of *Inst_Q*. Considering the high R^2, this means that institutional quality is likely to have approximately the same importance of the value of the imports from China for the variation in the stock patents. This is consistent with what past literature tells us about the importance of the quality of institutions for national innovation (especially when this is expressed by IPRs). However, the highest coefficient (1.585) is that of the R&D expenditure. This is reasonable without any doubt, since R&D is the most important direct input for innovation.

We also checked if this long-run relationship of the stock of patents with *ln(impchina)* and *Inst_Q* was robust to the distinction among different geographical contexts and the relationship of *ln(stockpatpop)* with both variables was still significant and, in some cases, quite strong.

In the North-Europe area, the resulting relationship with the quality of institutions is almost four times the one with the import variable. The explanation could lay in a possible better and stronger support of national innovation by the institutions, so that the system is more based on them than on other factors.

In Western Europe, the only significant relationship is with imports, which do not even impact on innovation as much as in the other areas. One explanation could lay in the variable concerning the R&D expenditure, which was not included in this specific analysis, in order to focus our attention more on the comparison between the impact of imports and of institutions. Countries in Western Europe may also be more affected by other factors we did not include in our analysis, such as, for example, the value of human capital. Unfortunately, we were not able to include this variable due to lack of availability of the data related to the period of analysis.

Also in the South of Europe, the relationship with the imports is strong (coefficient equal to 1.441), but the one with the quality of institutions is not significant. Indeed, the quality of institutions is lower than in the other areas, so we may expect that this lack of support to innovation is compensated by a larger impact of imports, for example, with more urgency in defensive innovation in order to survive in a more competitive context, or more developed capabilities in absorbing knowledge from abroad (considering that the knowledge spillover is one of the possible effects of an increase in imports). Moreover, in this specific part of the analysis, we consider all types of patents (not just the high-tech ones): manufacturing employment in the Southern countries "is predominantly concentrated in SMEs and low-tech sectors" (Donatiello and Ramella, 2017, p. 172), and our patent count, in the case of such countries, could be inflated by such lower-tech innovations. "Because this model is associated with a system of incremental innovation, which is less dependent on education systems and research, this might explain why Southern Europe companies are still able to innovate despite the weaknesses of their respective NIS" (Donatiello and Ramella, 2017, p. 172). Anyway, the investigation of the reason of such gap between the South and the rest of Europe in the impact of the two factors on innovation may be the starting point for future research.

In the US, both relationships are strong. However, in this specific case, the sample is limited to the time series of the US, so with a much lower number of units, thus, giving less reliability to the specific analysis.

We also checked for the same geographical-specific relationship in the case of high-tech patents.

In Northern Europe, we find a much stronger impact of institutions comparing to imports, as in the previous case.

In Western and in Southern Europe, like for the total stock of patents, the only significant relationship is with imports, but, in this case, imports turn out to have a much larger impact on innovation.

In the US both relationships are significant, but imports have a much larger impact comparing to the quality of institutions. In fact, their coefficient related to imports from China reflects the difference between their *impchina* (the Chinese import penetration, meaning the share of imports from China with respect to the total imports) and that of the other countries. We may conclude that a very large import penetration from China is likely to lead to a much larger elasticity in the log-log relationship, that is a much larger impact of one additional percentual variation on high-tech innovation.

In any case, for the European countries, our results seem to be quite consistent with those of Bloom *et al.* (2016), who analyzed the impact of the imports from China on innovation (measured by patent counts) in twelve European countries (ten of which are also included in our analysis). Their results are also significantly positive, although the period of analysis is much shorter than ours.

If we compare our results specifically for the US with those found by Autor *et al.* (2020), they are the opposite. Indeed, the relationship of imports from China with patents in their analysis was found to be negative. However, we believe that some very important aspects failed to be considered.

In their analysis, in addition not to considering R&D expenditure among the explanatory variables, Autor *et al.* (2020) also did not take the institutional factors into account. As we deepened in the literature review, institutions are defined as the rules of the game in a society (Barbosa and Faria, 2011; North, 1990) and they also surely influence aspects related to IPRs, and, consequently, their volume. That is why high institutional quality is likely to facilitate and incentivize such phenomenon and affect its volume (Barbosa and Faria, 2011; Cunningham *et al.*, 2019; Taylor, 2009; Varsakelis, 2006; Zhu and Zhu, 2017). Indeed, in our analysis, the variable *Inst_Q* was always significantly and strongly correlated with the patent count, and the relationship was the strongest in the US.

Moreover, Autor *et al.* (2020) did not take patents from non-listed firms into account for their dependent variable, and we believe that this may have affected their results.

If we compare our results in the Western area with those of the study of Vancauteren *et al.* (2019), who analyzed the effect of imports from China on innovation (measured by patents) in the Netherlands, we also find them to be contrasting. Nevertheless, the authors also did not take the impact (which was high in our Western-countries analysis as well) of the quality of institutions into account, and we believe that this may have biased their results. Moreover, our analysis involved more than one country, while theirs is specifically focused on the Netherlands, which means that variables and results may be affected by specific characteristics of the country, thus the comparison between the analyses is not much relevant.

3.3.3 Short-run causality

Our findings show that a positive variation in the value of imports from China Granger causes an increase in the stock of patents per capita in the short term. This is consistent with what we expected, and also with some important theoretical effects we presented in the literature review.

First, we find it in line with Arrow's "displacement effect" (also called "escape-competition effect"), where imports are considered a source of competition and such competition is expected to push innovation by reducing the pre-innovation rents, that is, the rents a firm can get without reacting with innovation (Aghion *et al.*, 2005; Arrow, 1962; Bloom *et al.*, 2016; Shu and Steinwender, 2019). Thus, firms are expected to face this market pressure by innovating more, because otherwise they may further lose market share and profit (Gonchar and Kuznetsov, 2018; Wang and Blomström, 1992; Lu and Ng, 2012). We believe that this reaction is due to the urgency of surviving in a more competitive context, thus it may be considered as a short-run effect.

Moreover, past findings (Hombert and Matray, 2018; Shu and Steinwender, 2019) show that such escape-competition effect prevails on the opposite Schumpeterian effect when the context does not include firms that are very far from each other in the technological frontier: in our sample we included higher and lower-tech-based countries, but we have no mix between, for instance, highly-developed and still-developing countries, so we expect that escape-competition effect tends to be dominant on the Schumpeterian one.

We also find that, in some cases, this short-run causality may be given by a component of the so-called "preference effect", just because of the urgency to react for the sake of the survival of the companies: managers perceive a threat for their job position, consequent to the uncertain survival of the firm they work in, due to the increased competitive pressure. Thus, they may be incentivized to put a larger effort on innovation (Hart, 1983; Raith, 2003; Schmidt, 1997; Shu and Steinwender, 2019; Vives, 2008).

Results of the short-run-causality test also show that there is no Granger causality of innovation on imports from China in the short run. Thus, we can say that the sudden and rapid growth in innovation in the early 2000's was due to the absolutely exogenous shock caused by China's enter into the WTO.

3.3.4 Long-run causality

In the long term, we found the causal relationship between imports from China and innovation to be mutual.

Without any doubt, imports from China Granger cause and stimulate innovation, and the results of our tests are consistent with some important effects we mentioned in the literature review.

First of all, we know that an increase in imports causes a tougher competitive environment, and the *Oslo Manual 2018* (OECD/Eurostat, 2018) suggests that such an intense competition can result in shorter product life cycles. Thus, firms are fostered to update their products frequently, causing a higher rate of product innovation. We expect this effect to be in the long term.

Another medium-long-term effect we expect to see after an increase in imports from China is the so-called "market-expansion effect". Indeed, a group of authors (Bloom *et al.*, 2016; Krugman, 1980; Schmookler, 1966) stresses the importance of eliminating trade barriers in order to enlarge market size and, in the long-term, spread the fixed costs of the production of each type of good among a larger number of competitors, thus allowing them to change their cost structure and shift such resources from the coverage of the fixed costs to the investment in innovation.

In the long run, innovation can be stimulated by imports thanks to a knowledge spillover. The import of goods can allow to have access to knowledge from some areas that are not necessarily just close to the borders of the domestic country. New knowledge can also simply consist of a better product mix, resulting from higher variety and lower costs of the inputs. In our case, we find this hypothesis more likely to explain this long-run causality, comparing to a possible proper knowledge gap (involving new technological skills, for example) to be filled by China in the countries of our sample, since they are all developed countries.

However, our results show also that the long-run Granger causality is mutual, meaning that, in the long term, imports from China themselves are also attracted by innovation in our group of OECD countries.

One possible explanation could be given by innovative firms adjusting their cost structure in the long term and buying more and more inputs from countries with a comparative advantage in production of inputs, thus selling such inputs at a lower cost. In this case, such innovative firms would gradually switch their supplier base to the Chinese area.

Moreover, if innovating is beneficial for firms, then we can reasonably expect that countries with higher innovation output have more monetary resources, pushing Chinese companies to enter a potential attractive market and export more.

Anyway, the causal relationship in this specific direction may be an interesting starting point for future research, which could deeper investigate the factors behind this phenomenon.

4. Conclusions and limitations

The fundamental scope of this empirical study was to investigate the relationship between imports from China and innovation across a sample of advanced economies, since analyzing several sources from the past literature gives no certain and univocal answer.

Our analysis consisted of several empirical tests investigating such relationship in a 25-years period (from 1995 to 2019) and across 15 countries (e.g., the US and 14 European countries).

Results show that imports from China and innovation (measured by patent counts) not only follow the same trend but are also linked by a long-run relationship, also robust to control variables, such as the quality of institutions and the R&D expenditure. Such relationship is still significant and strongly positive when we split the sample by pooling countries into macro-regions.

Final tests show that there is also a causal relationship between the two variables: in the short run a positive variation in the value of imports from China (Granger) causes a growth in the number of patents, and the causality is in this direction only, suggesting that the sudden growth in innovation in the early 2000's was due to an exogeneous shock when China entered the WTO and increased its exports towards the OECD countries. In the long run, the causal relationship is mutual. The idea of imports from China as determinant of innovation, both in the short and in the long run, finds consistent explanations in many aspects of the literature we revised. The increase in imports caused by positive variations in the long term may be possibly explained by the shift of innovative firms from their usual supplier base to the Chinese supply market, which offers low-cost inputs.

Nevertheless, this empirical study is not without limitations.

First, as we also explained in the literature review, patents as a proxy measure for innovation have some shortcomings. Although, considering the other possible proxies that we also mentioned in the literature review, patents are still a valid choice for innovation measure in such a study, results would be likely to be slightly different if we performed the same type of analysis but choosing a different measure for firms' innovational activity.

A second limitation of our analysis may concern possible omitted variables, that were included in the error term, for example the quality of human capital across the countries. However, unfortunately, we found no available data for our period of analysis in the databases which usually collect such data. In any case, we believe that our *Inst_Q* variable (which is, in turn, the average of six WGIs) already summarizes many aspects of the different national contexts, which are likely to affect the dependent variable. In addition, controlling also for R&D expenditure, year-specific and country-specific fixed effects, and normalizing some variables for population or GDP should acceptably reduce possible biases (this is also confirmed by the high R^2 resulting from the tests).

Another possible limitation could concern the variable *Inst_Q* itself: in a more precise analysis, this mean could be replaced by six different control variables representing the six WGIs themselves.

However, this study may be the starting point for future research, which may focus on investigating factors behind the long-run Granger causality of innovation for changes in imports from China, or performing analyses similar to ours, but overcoming some of the limitations we mentioned before, such as including the human capital component among the control variables or including all the six distinct indicators for institutional quality.

Anyway, despite some shortcomings, this empirical research gives a contribute by filling a gap in the literature. To our best knowledge, there is no past study on this topic which includes a panel of countries (and not just focused on one) and considers institutional quality as control variable. Moreover, the past analyses which are the most similar to ours are focused on the significancy and of the sign of the relationship between innovation and Chinese imports, but do not deepen the concept of causality and its direction, neither in the short nor in the long run.

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