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Importer Dynamics: Do Peers Matter?

Abstract

Few firms import, even when formal trade barriers are low and despite substantial potential gains. Likely reasons are uncertainty and informational frictions, creating scope for local peers to affect new importers. We explore this hypothesis using data on French imports by firm-product-country-year, location, and importer characteristics. First, we study the decision to start importing as a function of the lagged number of importers in the same commuting zone (CZ). We find that the presence of such peers more than doubles the probability to start importing the same product from the same country. The effect increases disproportionately with the number of peers. Second, we examine how the elimination of Multi-Fibre Agreement textile and clothing quotas affects the number of import starters at the CZ level. Here the number of import starters from quota countries increases by 40 to 90% more in commuting zones with a higher initial number of peers.

JEL-Codes: F140, F610, D220.

Keywords: trade, import start, spillovers, peer effects, Multi-Fibre Agreement.

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1 Introduction

Imports provide firms with access to cheaper inputs and can also be a source of productivity gains in the form of additional input varieties, higher input quality and/or embodied superior knowledge.[1] Despite this, few firms import. In the French data we use in this paper only about 4 percent of all firms import,[2] in spite of access to multiple neighbor countries in the Single European Market without legal trade barriers and with the same currency. Theoretical frameworks with large sunk costs and complementarities at the extensive margin of trade can explain why so few firms trade,[3] but observed deviations from strict sorting of firms into trading status and deviations from exact hierarchies in products and countries suggest that additional factors matter for explaining import and export choices (Eaton et al., 2011; Armenter and Koren, 2015). One possible explanation for the rarity of imports is that they involve trade barriers of another nature, such as uncertainty on the availability or reliability of suppliers, or search and matching frictions. If this is the case, non-importers may learn from existing importers, either by way of information diffusing through personal networks or through movements of workers with import-specific knowledge. While research has shown that such *peer effects* matter for exports, see e.g. Aitken et al. (1997); Fernandes and Tang (2014); Maurseth and Medin (2017); De Lucio et al. (2020); Mendoza (2022), much less attention has been given to spillovers in imports.[4] The presence of such spillovers would make a case for devoting similar resources to import promotion as countries currently dedicate to incentivizing firms to start exporting. Spillovers of this nature may also help our understanding of movements of workers and wage heterogeneity within industries.

In this paper we examine the following question: is a firm's decision to start importing affected by the import activity of its local peers, and if so, how? To examine the hypothesis that new importers are influenced by the behavior of local importers, we use highly disaggregated French data. In particular, we match data on import transactions by firm-product-country-year (Customs), balance sheet data and firm location information from firm's tax returns (FICUS) and data on business groups and firm ownership (LIFI survey). We conduct two empirical exercises. First, we examine the decision of an individual firm to start importing as a function of the number of

[1] See among others Amiti and Konings (2007); Kasahara and Rodrigue (2007); Haller (2012); Gopinath and Neiman (2014); Halpern et al. (2015); Blaum et al. (2018).

[2] This is calculated across the population of firms and sectors, comparable figures in the literature often refer to a specific sector or to firms above a certain size threshold.

[3] Research on trading firm dynamics emphasizes large exporting and importing startup costs (see among others Das et al. (2007) and Kasahara and Lapham (2013)), and predicts that only the largest and most productive firms engage in international activity. Furthermore, complementarities between decisions to export and import additional products to/from additional countries can magnify initial productivity differences (Bernard et al., 2018).

[4] Exceptions include López and Yadav (2010); Bisztray et al. (2018); Békés and Harasztosi (2020); Hu and Tan (2020). We discuss our contribution relative to these articles below.

local peers. Second, we analyze whether the number of import starters differs in commuting zones with many versus few established peers following an episode of trade liberalisation.

For the first exercise, we consider the number of importers in a commuting zone of a certain product from a certain source country. We estimate the effect of that number of importers on the probability that a firm in the same commuting zone starts importing the same 4-digit HS product from the same source country in the following year. We use the lagged number of importers as the information may take time to diffuse. To control for confounding factors we make use of firm-year, country-year and product-year fixed effects. The firm-year effects control for anything that is specific to a firm in a particular year, e.g. differences in industry, location, firm size, ownership, productivity. Thus, the spillover effect is identified from firms being exposed to source country variation in their peers' importing patterns.

In our preferred specification we find that the presence of peers importing the same product from the same source country located in the same commuting zone more than doubles the probability to start importing. This probability increases as the number of existing importers in the same commuting zone increases; it does so in a highly non-linear fashion. In addition, we show that recent import starters also generate spillovers. When we aggregate imports over all products or over all source countries, we find robust results for the presence of importing peers, but an additional peer has a lower influence. When aggregating to the firm level the effect vanishes. Similarly, the number of peers outside the importer's sector does not affect the likelihood of starting an import relationship. This suggests that peer influence is restricted in scope.

We find some heterogeneity in peer influence. In particular, larger and younger firms are more likely to start importing in the presence of peers. Likewise, the presence of larger, more productive peers, or peers that have a higher export intensity and are younger has greater influence. Furthermore, peer effects are stronger for countries that do not share a common border with France or that are not fellow members of the European Economic Area (EEA).

Given our identification strategy and our controls for unobserved country-year and product-year factors, the presence of peers is unlikely to operate through product or factor market competition channels. We also rule out that coordinated import decisions with local firms that belong to the same business groups are the only source of peer effects. In contrast, our findings are consistent with the information transmission channels highlighted in the literature: namely, that import starters overcome informational frictions by learning from observing local peers, and/or by poaching workers with import-relevant experience and skills from these local peers.[5]

Our second empirical exercise leverages a 'quasi-natural experiment' that caused shocks to the

[5] See among others Fernandes and Tang (2014); Kamal and Sundaram (2016); Mion and Opromolla (2014) and Meinen et al. (2022) for evidence of both channels operating in the case of exports.

costs of importing goods into France: the phased elimination of textile and clothing quotas from the Multi-Fibre Arrangement (MFA) in the late 1990s and early 2000s. We examine how this policy change affects the number of import starters of previously quota-restricted products at the commuting zone (CZ) level. Because MFA quotas were administered at the level of the European Union, the policy change is plausibly exogenous from the viewpoint of French importers. This second exercise therefore lends itself to a causal interpretation. A drawback, however, is the limited sectoral coverage, as only importers of textile and clothing products were affected.

For this exercise we adopt a difference-in-difference methodology. We leverage the wide heterogeneity across CZs in their exposure to imports of a given product from a given country prior to the experiment, to create a high-exposure treatment group and a low-exposure control group. We hypothesize that the former will respond more strongly to quota elimination. Our estimates confirm this hypothesis with average treatment effects implying 40-90 percent increases in the number of import starters per product-country combination and commuting zone following the 2002 and 2005 phases of MFA quota eliminations. In both phases the effects persist until the end of the sample period.

As mentioned peer influence has received considerable attention in relation to the decision to start exporting. In contrast, few papers have been devoted to the decision to start importing. Exceptions include López and Yadav (2010); Bisztray et al. (2018); Békés and Harasztosi (2020); Hu and Tan (2020).[6] López and Yadav (2010) find that Chilean firms are more likely to import when there are many importers in the same 3-digit industry and the same region. Bisztray et al. (2018) show that the number of importing peers located in the same street of Budapest, or with managerial or ownership connections, increases the probability to start importing. Békés and Harasztosi (2020) find evidence of import spillovers among Hungarian importers of the same type of manufacturing machinery. Hu and Tan (2020) find that Chinese firms are more likely to start importing when neighbors importing the same product from the same country experience a price fall. Our contribution relative to these papers is two-fold. First, we exploit a change in trade policy to examine the causal impact of peer import activity. Second, the scope of our analysis is broader. We use national data in a large economy on multiple product categories, as opposed to a single city (Budapest) or a single product category (machinery).

Our paper also relates to a recent research agenda on firm-level models of import decisions, e.g. Kasahara and Lapham (2013); Halpern et al. (2015); Antràs et al. (2017); Koren and Armenter (2017); Blaum et al. (2018). Influence from peers provides a complementary explanation as to why observationally similar firms differ in their importing behavior.

[6]Huremović et al. (2022) study how domestic suppliers and customers in a firm's production network affect its propensity to start importing.

The paper is organized as follows. Section 2 presents the data and the empirical methodology. Section 3 presents results of our individual firm exercise, while Section 4 reports results of our natural experiment. Section 5 concludes.

2 Data sources

Data are assembled from four main primary sources. First, we extract balance sheet data on all French firms submitting tax returns in 1996-2007 from the *Fichier Unifié de SUSE* (FICUS) dataset. We also extract information on the location of each firm's headquarters across France's 348 continental commuting zones for each firm-year. Throughout the analysis we exclude firms in the wholesale and retail distribution sectors (NACE rev 1.1. 50-52 industries).[7] We also report some results on firms not owned by business groups. This information comes from INSEE's Liaisons Financières (LIFI) survey.

The third dataset comes from French Customs (DGDDI). This dataset provides exhaustive records of French imports at the firm-country-CN8 product-year level between 1996 and 2007.[8] Some standard cleaning steps are performed on the raw data.[9]

The commuting zone level exercise in addition relies on the European Commission's SIGL (Système Intégré de Gestion de Licences) database on licenses for textile and clothing import quotas.[10]

We use the data to assess whether peer effects matter using two different sources of variation in the data. For the first exercise we estimate peer effects at the level of the individual firm. The second exercise is estimated at commuting zone level using variation from the stepwise elimination of EU import quotas associated with the Multi-Fibre Arrangement in 1998, 2002, and 2005. We describe each of these in turn and provide information on how we use the data for each exercise below.

[7] See however a robustness check with peers from the wholesale and retail sectors in Section 3.4.3.

[8] We end our panel before 2008 which brought changes in the collection of balance sheet data as well as a major trade collapse. In addition, commuting zones were redefined in 2010.

[9] See Bergounhon et al. (2018) for a presentation of the dataset and the cleaning procedure.

[10] These data have been used to evaluate the impact of MFA quota elimination by De Loecker (2011) and Utar (2014) among others. The original data are classified according to 163 quota product categories, which we match to the EU's Combined Nomenclature 8-digit (CN8) product classification. We are grateful to Geoffrey Barrows and Jan De Loecker for sharing this data with us.

3 Firm-level exercise

3.1 Specification

At the firm level we examine the impact of peers located in the same commuting zone on a firm's probability to start importing the same HS4 product from the same source country:

$$ImpStarter_{irpct} = \alpha + \beta NImp_{rpc,t-1} + \lambda_{it} + \lambda_{pt} + \lambda_{ct} + \varepsilon_{irpct}, \quad (1)$$

where i indexes firms, r commuting zones, p products, c source countries, and t time. $ImpStarter_{irpct}$ is a dummy variable that takes the value 1 if firm i starts to import product p from country c in year t, and 0 otherwise. This includes firms that start importing for the first time, but the majority of firms add countries or products. We control for firm-year λ_{it}, product-year λ_{pt}, and source country-year λ_{ct} fixed effects.

The variable of interest is $NImp_{rpc,t-1}$, the number of firms located in the same commuting zone that imported the same product from the same country in $t-1$. We estimate different specifications of equation (1) using a linear probability model. We take a positive β coefficient as evidence that the presence of peers increases the probability to start importing. The country-year fixed effects absorb everything that is specific to a particular source country in a particular year, such as country-specific business-cycles that might affect import supply in a particular year. Considering that all imports are into France, these fixed effects also absorb origin-destination-specific factors such as exchange rates, size (GDP), trade barriers and other 'gravity' determinants of trade flows. Likewise, the product-year fixed effects capture product-specific demand or supply patterns beyond the control of an individual importer. We further include firm-year fixed effects, these capture anything that is specific to the firm, its location (CZ) and its industry in a particular year.

The main concerns to identification in this setting are endogenous peer groups, omitted variables, and the reflection problem (Manski, 1993). First, as we use the 348 commuting zones to partition the space of continental France, peer groups might be endogenous. if firms from one industry or firms with a high propensity to import co-locate and make similar import decisions, this may result in a spurious correlation between $NImp_{rpc,t-1}$ and ε_{irpct}. Second, omitted variables may result when particular locations are better for importing from a specific country c. Third, a reflection problem can emerge because individual i's residual in equation (1) enters indirectly in the regressor $NImp_{rpc,t}$, thus violating the orthogonality condition. This is because any peer j's value of $ImpStarter_{jrpct}$ depends on the number of its peers, which includes i.

Our preferred specification addresses these concerns as far as possible. First, the coefficient estimates are identified off within-firm-year variation in the number of peers across countries and products. Thus endogenous peer composition would require firms to co-locate in order to start importing in at least two identical country-product pairs. Second, the set of fixed effects also accommodates omitted unobserved sector-year or commuting-zone-year characteristics, such as changes in industry concentration, local factor supply or local transportation costs. In other words, interaction with peers on local factor or output product markets should not affect our estimates. Third, the use of a lag of the number of peers alleviates the reflection problem, as suggested by Manski (1993). Doing so implies that $ImpStarter_{irpct}$ depends on the *second* lag of ε_{irpct} through reflection. Thus it only poses a threat to identification if ε_{irpct} and $\varepsilon_{irpct-2}$ are correlated.[11] As will be explained below our sample excludes observations after an import relationship is established, as will be explained below. In this context, assuming no serial correlation in ε_{irpct} amounts to assuming that firms *yet to enter* a *cp* import relationship are subject to an independent random shock every year.

3.2 Data preparation

For the firm-level exercise we take several steps to reduce the computational burden emerging from the high dimensionality of the data. First, we aggregate all imports to the HS4 digit level. Second, we restrict the analysis to the ten source countries that each account for more than 2 percent of the share of matched French imports over the sample period.[12] Together these countries account for 72 percent of matched imports. We further restrict the number of products for this set of countries, by selecting all products with a share in excess of 0.5 percent in the country sample over the period. This yields 21 HS4 products that together account for 13.6 percent of the full sample of matched imports over the period 1996-2007.[13] These products span across a wide range of sectors, including pharmaceuticals, iron and steel, parts of nuclear reactors, computer equipment, electrical machinery, transport equipment, and furniture.

As we examine the decision of an individual firm to start importing, we square the data by filling in missing cells for firm, HS4 product, source country and year. We keep observations up to and including the year a firm starts to import.

[11]For robustness we also estimate a model with the number of peers lagged by two periods. Results are reported in Section 3.4.3.

[12]The set of countries is Belgium-Luxembourg, China, Germany, Great Britain, Italy, Japan, Netherlands, Spain, Switzerland, and the United States.

[13]The list of HS4 products is 2402, 2709, 3004, 7208, 8409, 8411, 8413, 8471, 8473, 8481, 8517, 8525, 8542, 8701, 8703, 8704, 8708, 8802, 8803, 9018, 9403.

Table 1: Firm-level characteristics of importers and import starters

	importers	import starters[1]
N	11041	6354[2]
empl	293	389
sales (mio EUR)	72.8	95.4
firm age	29.1	28.0
share exporters	75.1	74.0
import value by HS4 product (mio EUR)	35.4	2.3
N markets	2.0	2.1
N products	1.7	1.9

Annual averages over the period 1997-2006 in the analysis sample.
[1] An import starter is defined as a firm that starts an import relationship (new product-source country) in the current year.
[2] Average number of unique firms that have import starts.

3.3 Summary Statistics

In the restricted dataset import starters account for one percent of importers and for just under one percent of import value. Table 1 provides summary statistics on importers and import starters in this sample. Import starters are firms that start one or more new import relationships at product-source country level. As some firms start more than one new import relationship, the table reports the firm level statistics by unique firms without weighting by the number of import starts. Import starters are somewhat larger than importers in terms of the number of employees and sales, they are marginally younger and less likely to also be exporters. Per HS4 product the value of their imports is lower, but they import from roughly the same number of markets and import about the same number of products on average.

Table 2 shows the number of import starts for all years in the sample. In total there were 96,808 import starts (new HS4 product-source country combinations) over the period of analysis. The Table also reports the distribution of the number of peers, which is computed by HS4 product-source country-commuting zone triple. In commuting zones with peers, on average an import starter has 15 peers who imported the same HS4 product from the same source country in the previous year. The median import starter has four peers; the distribution is highly skewed to the right. There is also a significant share of import starters in commuting zones without peers. Note that numbers of peers vary across product-country-zone combinations and over time, and both sources of variation matter quantitatively.[14]

[14]Decomposing the variation of the number of peers by country-product-zone-year yields a 1.368 'within country-product-zone' standard deviation, to be compared with the overall 5.639 standard deviation.

Table 2: Import starts and the distribution of peers

	Starts	Distribution of the number of peers in $t-1$						% cells
	N	mean	min	p25	p50	p75	max	w/o peers
1997	10269	16	1	2	4	14	215	62.5
1998	10452	16	1	2	4	14	235	61.2
1999	10322	16	1	2	4	14	206	61.0
2000	10504	18	1	2	4	14	228	61.0
2001	9476	17	1	2	4	14	237	61.1
2002	9072	14	1	1	4	13	208	60.6
2003	8320	11	1	1	3	11	172	61.5
2004	9251	13	1	1	4	12	208	60.7
2005	9431	14	1	1	4	12	213	60.4
2006	9711	13	1	1	4	12	207	60.1
All years	96808	15	1	1	4	13	237	61.1

Notes: 'Peers' refer to firms located in the same commuting zone importing the same HS4 product from the same source country in $t-1$. The distribution of the number of peers is conditional on having at least one peer.

3.4 Evidence of peer effects on import starters

3.4.1 Main results

We start by assessing whether the *presence* of peers importing the same HS4 product from the same source country affects the probability of firms located in the same commuting zone to import the same product from the same source country. For this purpose we replace the number of peers $NImp_{rpc,t-1}$ in equation (1) with a dummy variable equal to 1 if the import starter is located in a commuting zone where there were peers importing the same product from the same source country in the previous year, 0 otherwise. The results are presented in the top panel of Table 3. To gauge the importance of different types of shocks we estimate equation (1) with different sets of fixed effects starting without fixed effects added in column 1. Columns 2-4 indicate that product-year and firm-year fixed effects contribute most to explanatory power, whereas product-year and source country-year fixed effects affect the coefficient of interest most. Note that the inclusion of firm-year fixed effects implies that we identify off variation across country-product combinations within a firm-year. This specification abstracts from commuting zone or commuting zone-year specific variables as well as from competition in the product market which is firm-year specific.[15] In column 5 we report a specification with country-product-year fixed effects. This specification relies on between-firm variation and requires at least two firms in two different commuting zones

[15]Consequently estimates that include commuting zone or commuting zone-year fixed effects are very similar to the results in column 4 with firm-year fixed effects and are available on request.

to start importing. It does not abstract from commuting zone characteristics. Our preferred specification in column 6, includes firm-year, product-year and source country-year fixed effects, which implies that we identify off within firm-year variation in the number of peers for the same firm starting two new import relationships. In this specification, the coefficient on the presence of peers is positive and significant. It indicates that being located in a commuting zone where peers that imported the same product from the same source country in the previous period are present more than doubles the baseline probability of starting to import (.00146/.00095 amounts to a 154 percent increase).

Table 3: Presence and number of peers

	(1)	(2)	(3)	(4)	(5)	(6)
Dep var:	Dummy = 1 if import start					
Presence of peers						
$\mathbb{1}(NImp > 0)_{rpc,t-1}$	.00230	.00211	.00145	.00296	.00086	.00146
	(.00025) **	(.00024) **	(.00022) **	(.00014) **	(.00015) **	(.00015) **
constant	.00063	.00070	.00095	.00038	.00118	.00095
	(.00003) **	(.00003) **	(.00002) **	(.00005) **	(.00002) **	(.00006) **
R^2-adj	.0008	.0012	.0017	.0075	.0033	.0086
Number of peers						
$NImp_{rpc,t-1}$	.00016	.00015	.00014	.00020	.00009	.00015
	(.00003) **	(.00003) **	(.00002) **	(.00004) **	(.00002) **	(.00003) **
constant	.00103	.00106	.00111	.00093	.00126	.00108
	(.00010) **	(.00009) **	(.00008) **	(.00010) **	(.00004) **	(.00007) **
R^2-adj	.0018	.0020	.0025	.0086	.0036	.0095
Obs	71,272,152					
mean Dep var	.00151					
country-year FE	no	yes	no	no	no	yes
product-year FE	no	no	yes	no	no	yes
country-product-year FE	no	no	no	no	yes	no
firm-year FE	no	no	no	yes	no	yes

Standard errors clustered at CZ level in parentheses. ** p<0.01, * p<0.05, (*) p<0.1

In the bottom panel of Table 3 we estimate equation (1) with the number of peers $NImp_{rpc,t-1}$ as the main explanatory variable using the same combinations of fixed effects as for the presence of peers in the top panel. These results confirm that there is a positive relationship between the number of peers in the commuting zone and the probability to start importing the same product from the same country. The coefficient estimate from our preferred specification in column 6 indicates that the presence of an additional peer in the same commuting zone importing the same product from the same country increases the probability to start importing by 9.9 percent. We refer to this as our baseline specification in the following.

We saw in Table 2 that the distribution of the number of peers is highly skewed. Whether the effect of peers' imports are indeed linear, as we posit in Equation (1), will matter. A simple way to assess the presence of non-linear effects is to create bins based on the number of peers.[16] Results are presented in Table 4. They indicate that the relationship between the number of peers in a commuting zone and the probability to start importing is highly non-linear. Going from 0 to 2-5 peers in the same commuting zone, increases the probability to start importing the same product from the same country by a factor four. The effect increases steadily with the number of peers. For instance moving from no peers to 11-20 increases the probability to start importing more than 7-fold. At 41 or more peers a firm is over 21 times more likely to start importing the same product from the same country.

Table 4: Number of importers binned

	(1)		(2)	
Dep var:	Dummy = 1 if import start			
$\mathbb{1}(NImp = 0)_{rpc,t-1}$	omitted category			
$\mathbb{1}(NImp = 1)_{rpc,t-1}$	.00202	(.00026) **	.00192	(.00015) **
$\mathbb{1}(NImp = 2-5)_{rpc,t-1}$	.00214	(.00042) **	.00226	(.00023) **
$\mathbb{1}(NImp = 6-10)_{rpc,t-1}$	.00248	(.00073) **	.00300	(.00054) **
$\mathbb{1}(NImp = 11-20)_{rpc,t-1}$	.00310	(.00087) **	.00376	(.00086) **
$\mathbb{1}(NImp = 21-30)_{rpc,t-1}$	.00448	(.00120) **	.00487	(.00128) **
$\mathbb{1}(NImp = 31-40)_{rpc,t-1}$	.00539	(.00118) **	.00548	(.00141) **
$\mathbb{1}(NImp = 41+)_{rpc,t-1}$	.01114	(.00137) **	.01103	(.00158) **
constant	.00059	(.00003) **	.00052	(.00014) **
R^2-adj	.0017		.0094	
Obs	71,272,152			
mean Dep var	.00151			
country-year FE	no		yes	
product-year FE	no		yes	
firm-year FE	no		yes	

Standard errors clustered at CZ level in parentheses. ** p<0.01, * p<0.05, (*) p<0.1

As we have seen the number of existing importers does increase the probability of additional firms to start importing. In Table 5 we investigate to what extent it is peers that recently started to import the same product from the same country that matter in this process. The idea is that new importers may learn more about different informational frictions from fellow import starters than from long-time importers. To examine this question, we define the number of peers variable based only on firms that started to import the same product from the same source country in the previous year. The results indicate, as for the effects from all importers with previous experience,

[16] In Section 3.4.3 we also present estimates from a logit model.

that the presence of recent import starters in the commuting zone increases the probability to start importing the same product from the same country by 133 percent. An additional recent import starter increases the probability to start importing by 22.5 percent in this specification. Thus, the effect of an additional recent import starter on the probability to start importing is stronger than that from an additional experienced importer.

Table 5: Peer effects from import starters

	(1)			(2)		
Dep var:	Dummy = 1 if import start					
$\mathbb{1}(NImpStarter > 0)_{rpc,t-1}$	.00148	(.00022)	**			
$NImpStarter_{rpc,t-1}$				.00034	(.00007)	**
constant	.00111	(.00006)	**	.00115	(.00008)	**
R^2-adj	.0086			.0094		
Obs	71,272,152					
mean Dep var	.00151					
country-year FE	yes					
product-year FE	yes					
firm-year FE	yes					

Standard errors clustered at CZ level in parentheses. ** p<0.01, * p<0.05, (*) p<0.1

3.4.2 Aggregation

As further exercises at the firm level, we aggregate, respectively, to the département level, over products and countries, and to the level of the firm. In Table 6 we first report results from aggregating to a higher geographical and administrative level, namely the département (96 in total). The estimated effects for both the presence (column 1) and the number (column 2) of peers are marginally higher than in the baseline. Aggregating over, respectively, products and countries, the results reported in Table 7 suggest that the presence of importers importing any product from the same country increases the probability to start importing by 23 percent (column 1). In turn, the presence of importers importing the same product from any country increases the probability to start importing by 19 percent (column 3). The effects are, thus, lower than the 97 percent increase at the country-product level. Furthermore, an additional existing importer importing from the same country increases the probability to start importing by 0.25 percent (column 2), while an additional importer importing the same product increases the probability to start importing by 0.44 percent (column 4). These compare to a 9.9 percent increase at the country-product level. These comparisons suggest that peer influence is strongest when importing the same product from the same country.

Table 6: Peers at département level

	(1)		(2)	
Dep var:	Dummy = 1 if import start			
$\mathbb{1}(NImp > 0)_{rpc,t-1}$	.00168	(.00015) **		
$NImp_{rpc,t-1}$			.00016	(.00003) **
constant	.00083	(.00006) **	.00095	(.00009) **
R^2-adj	.0087		.0090	
Obs	71,272,152			
mean Dep var	.00151			
country-year FE	yes			
product-year FE	yes			
firm-year FE	yes			

Standard errors clustered at département level in parentheses. ** p<0.01, * p<0.05, (*) p<0.1

Table 7: Aggregating to product and country level

	(1)	(2)	(3)	(4)
	All products		All countries	
Dep var:	Dummy = 1 if import start			
$\mathbb{1}(NImp > 0)_{rc,t-1}$	.00483			
	(.00047) **			
$NImp_{rc,t-1}$		.00005		
		(.00001) **		
$\mathbb{1}(NImp > 0)_{rp,t-1}$			.00183	
			(.00023) **	
$NImp_{rp,t-1}$				.00004
				(.00001) **
constant	.01617	.01638	.00835	.00807
	(.00043) **	(.00049) **	(.00016) **	(.00018) **
R^2-adj	.0557	.0523	.0265	.0244
Obs	3723580	3430720	7818368	7203378
mean Dep var	.02060	.01968	.00962	.00918
country-year FE	yes		no	
product-year FE	no		yes	
firm-year FE	yes		yes	

Standard errors clustered at CZ level in parentheses. ** p<0.01, * p<0.05, (*) p<0.1

Table 8: Aggregating to firm level

	(1)		(2)		(3)	
Dep var:			Dummy = 1 if import start			
$NImp_{i,t-1}$	-.000000	(.000001)				
$\mathbb{1}(NImpStarter)_{i,t-1}$			.015944	(.025750)		
$NImpStarter_{i,t-1}$					.000013	(.000005) **
constant	.159187	(.002240) **	.154029	(.025737) **	.153101	(.001934) **
R^2-adj	.2354		.2527		.2355	
Obs	412,489		340,463		412,489	
mean Dep var	.15844		.16697		.15844	
firm FE			yes			
year FE			yes			

Standard errors clustered at CZ level in parentheses. ** p<0.01, * p<0.05, (*) p<0.1

As a final exercise we aggregate to the firm level, that is we test whether the sheer presence and number of other importers (import starters) in the same commuting zone affects the probability to start importing. Table 8 suggests that this is not the case - neither for existing importers nor for import starters.[17] We take this to imply that information on the product, its origin or both are key ingredients for the presence of spillovers from importing.

3.4.3 Robustness

In this section we describe the results of a number of robustness checks, the corresponding tables are reported in the Appendix.

Share of peers We first test an alternative specification, where instead of using the number of importers or import starters in a commuting zone, we use the share of importer/import starter peers relative to the number of firms in a commuting zone as the explanatory variable. This gets at whether the presence of peers in relative or absolute terms matters. The results in Table A1 suggest that the number of importers relative to the number of firms in a commuting zone importing the same product from the same country does matter. Based on the coefficient estimate in column 1, a one percentage point increase in the share of established importers of the same product from the same origin increases the probability to start importing by five percentage points. Note, however that the average share of importer peers is 0.1. As the results from the binned regressions in Table 4 suggest that the effect is non-linear, we confirm this in this setting by including the square of the

[17]Note that there are importers in all commuting zones, hence the dummy exercise for the number of importers is mute. Further note that while the coefficient on the number of peers in column 3 is statistically significant, the implied increase is tiny: 0.008 percent.

share of importer peers in column 2. The effect of the share of import starter peers presented in column 3 is even larger - an implied 13 percentage point increase also this effect is highly non-linear (column 4).

Logit A second alternative specification is to fit a logit model instead of a linear probability model. This is a natural check given the binary dependent variable and the non-linearity suggested by Table 4.

Specifically we estimate the following model

$$log\left(\frac{Prob[ImpStarter_{irpct}=1]}{Prob[ImpStarter_{irpct}=0]}\right)=\alpha+\beta NImp_{rpc,t-1}+\varepsilon_{irpct}. \tag{2}$$

The coefficient estimate for β from the above model is 1.5375 (SE .0691), the log pseudolikelihood is -776434.42 (pseudo-R^2 = .04, constant -7.3671 (SE .05078). Figure 1 depicts the predicted values of $Prob[ImpStarter_{irpct}=1]$ evaluated at various values of $NImp_{rpc,t-1}$.[18] The figure confirms that the probability of an import start increases with an additional peer in a markedly convex way.

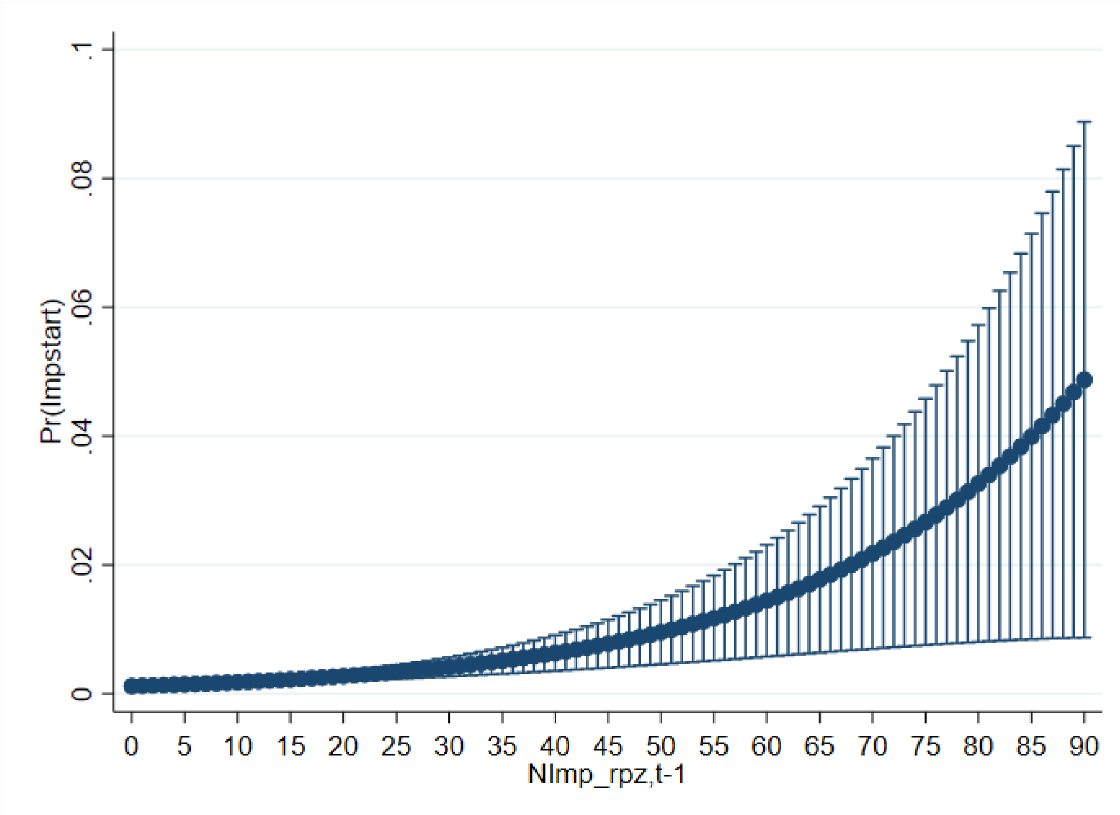
Second lag, Adding wholesale & retail sector peers, excluding Paris, and excluding sector-product combinations with no imports In Table A2 we present the results of four additional robustness checks.

First, we use the second instead of the first lag of the number of peers importing the same product from the same country. Note that using earlier lags of the number of peers alleviates the reflection problem, since reflection would require individual error terms to be correlated over longer periods of time. In the first column of Table A2 we report the baseline coefficient from the last column of Table 3. While the coefficient estimate for the specification with the second lag in column 2 is very similar, the implied effect in this naturally shorter sample is 12.9 percent.

Second, we consider peers that belong to the wholesale and retail sectors (NACE industry codes 50-52). These firms are omitted in the main analysis, but it is conceivable that in particular firms that switch from importing indirectly via a retailer or wholesaler to importing directly learn from these peers. Column 3 of Table A2 shows that the number of the wholesale and retail peers has no significant effect on the probability to start importing. Meanwhile, the coefficient on the manufacturing sector peers is very similar to the baseline.

[18] We truncate the figure at 90 peers for expositional reasons. Estimates of a variant of the model with firm controls yield identical estimates up to the fifth decimal place. These are available upon request.

Figure 1: Predicted probabilities to start importing estimated from the logit model (equation (2))



Note: Figure plots the predicted probabilities from the logit model in equation (2) at values of $NImp_{rpc,t-1}$ together with 95% confidence intervals out to 90 peers.

The predicted probabilities range from .0011973 with no peers to .0487842 with 90 peers.

Third, in column 4 we exclude the Paris commuting zone, which stands out for its high number of importers and import starters (recall that we define a firm's commuting zone as that of its headquarters, under the assumption that that is where decisions on imports are taken). Results are qualitatively unchanged and the coefficient of interest increases by roughly 50 percent.

Fourth, our analysis of import starts so far has allowed each firm to potentially import any of the 21 products considered in the analysis. However, some firm-product combinations are likely independent of peer influence, for example because the firm's production technology does not require that product. A concern could be that the inclusion of such products induces a spurious correlation between the number of peers and the probability to start importing. Therefore, we reconstruct our sample to exclude unlikely firm-product combinations. More precisely, we rule out imports of products that were not imported by any firm of the same NACE 3-digit industry over the sample period. This procedure excludes 1083 out of 3990 possible sector-product pairs and reduces sample size from 71.3 to 62.6 million observations. As column 5 of Table A2 shows, the results are only marginally smaller relative to the baseline.

Randomization inference As a last robustness exercise we randomize the allocation of the number of peers by product-source country combination across commuting zones within a calendar year and re-estimate our baseline model (eq. (1)). The distribution of coefficient estimates obtained from 1,000 replications of this exercise is reported in Figure A1. The estimated coefficient from our baseline specification lies well outside the distribution of the coefficients obtained when randomising. The two-sided empirical p-value from a permutation test of our baseline estimate against the coefficient estimates obtained from randomising is 0.000. This suggests it is highly unlikely that a similar size baseline estimate would have been observed under different hypothetical assignments of the peer variable.

3.5 Channels

We now turn to the question of possible channels through which the number of local importing peers affects a firm's decision to start importing.

Two channels of knowledge diffusion first come to mind. First, import starters may overcome informational frictions by merely observing their local peers, as was found by some studies on export spillovers (see e.g. Fernandes and Tang (2014)). Second, import starters may benefit from interactions with peers or acquire information or skills by hiring workers from firms with import experience, as shown for exports by Labanca et al. (2013); Masso et al. (2015); Mion and Opromolla (2014); Patault and Lenoir (2023).

Some alternative explanations are ruled out or made less plausible by some of our findings. For instance, recall that our main estimates are identified off within firm-year variation in the number of peers. As a result, all unobservable factors specific to the year and the import starter's industry, or to the year and the import starter's commuting zone, are accounted for. This includes time-varying commuting zone or industry characteristics capturing for example local product market and factor market competition, local transportation costs or industry concentration. In other words, mechanisms working through shocks to common trade costs or the intensity of product market or factor market competition cannot explain our results. One could also argue that new importers in a commuting zone are passively receiving information on import sources by non-peers such as exporting firms or specialized consultants. However, considering our identification strategy based on within-firm-year variation, that information would have to be specific to particular country-product pairs. In addition, we find higher coefficients in settings with more peers (see for instance Table 4) where sharing a single common source of information is less plausible. So while this mechanism might be at work in some instances, it is unlikely to be the key driver behind our estimates.

Table 9: Independent firms versus business groups

	(1)		(2)	
Dep var:	Dummy = 1 if import start			
$\mathbb{1}(NImp > 0)_{rp,t-1}$	.00226	(.00015) **		
$\mathbb{1}(NImp > 0)_{rp,t-1}$ × indep	-.00153	(.00008) **		
$NImp_{rpc,t-1}$			.00019	(.00003) **
$NImp_{rpc,t-1}$ × indep			-.00007	(.00001) **
constant	.00095	(.00006) **	.00108	(.00007) **
R^2-adj	.0087		.0066	
Obs	71,272,152			
mean Dep var	.00151			
country-year FE	yes			
product-year FE	yes			
firm-year FE	yes			

Standard errors clustered at CZ level in parentheses. ** p<0.01, * p<0.05, (*) p<0.1

Finally, some of the peer influence we observe may come from firms that are related to the importer. For instance, importers may have local peers that belong to the same business group, in which case importing decisions might be coordinated at the business group level. To investigate whether spillovers differ between firms that are part of business groups and independent firms we rerun the baseline model and include an interaction term that takes value 1 if the firm is independent according to the following definition: A firm belongs to a business group if the group has more than 50 percent of the control rights to the firm, whether directly or indirectly through other firms. We define an independent firm as a firm that does not belong to a business group. Just over 50 percent of the observations in our sample (37,645,88) come from independent firms. The results that include the interaction term for both the dummy and the continuous peer measure are reported in Table 9. Peer effects on the probability to start importing are stronger than in the baseline for firms that are part of business groups. Still the implied effect on the probability to start importing for the independent firms is a 76 percent increase (baseline: 148 percent) in the presence of peers; and an increase of 8 percent (baseline: 10 percent) due to an additional existing importer. We conclude that while magnitudes differ, peer effects are not merely due to coordination of importing decisions across firms belonging to a business group.

Import starter characteristics To shed more light on the mechanisms at work, we examine whether the presence of peers has a differential effect on the probability to start importing depending on import starter characteristics. As all types of firm characteristics are captured in the firm-year fixed effects, we generate dummy variables indicating whether a firm has high employment, sales, productivity (log of value added per worker), age, or is an exporter. More precisely, we split the sample at the current year's median value for each firm characteristic. We then interact these dummy variables with the number of peers.[19]

Results are reported in Table 10. Our estimates suggest that firms with the following characteristics benefit more from the presence of peers: large firms in terms of employment and sales, exporters, and younger firms. In the case of large firms and exporters, effects are large in the sense that the estimated coefficients more than double. In contrast, the effects for high-productivity firms are not significantly different from those of low-productivity firms.

Table 10: Import starter characteristics

	(1) emp	(2) sales	(3) prod	(4) export status	(5) firm age
Dep var:			Dummy = 1 if import start		
$NImp_{rpc,t-1}$	.00009	.00009	.00015	.00009	.00016
	(.00001) **	(.00001) **	(.00002) **	(.00001) **	(.00003) **
$\mathbb{1}(highemp) \times NImp_{rpc,t-1}$	.00013				
	(.00003) **				
$\mathbb{1}(highsales) \times NImp_{rpc,t-1}$		.00012			
		(.00002) **			
$\mathbb{1}(highprod) \times NImp_{rpc,t-1}$			.00000		
			(.00001)		
$\mathbb{1}(exporter) \times NImp_{rpc,t-1}$				.00014	
				(.00004) **	
$\mathbb{1}(olderfirm) \times NImp_{rpc,t-1}$					-.00003
					(.00001) **
constant	.00107	.00107	.00108	.00106	.00108
	(.00007) **	(.00007) **	(.00007) **	(.00007) **	(.00007) **
R^2-adj	.0097	.0097	.0095	.0097	.0095
Obs			71,241,310		
mean Dep var			.00151		
country-year FE			yes		
product-year FE			yes		
firm-year FE			yes		

Standard errors clustered at CZ level in parentheses. ** p<0.01, * p<0.05, (*) p<0.1

These results are consistent with several mechanisms related to informational frictions. A first possibility is that potential importers can resolve some uncertainty about potential new import

[19]Table A3 in the Appendix reports results of regressions with quartiles of import starter characteristics instead of a median split. Results are qualitatively similar.

relationships by observing their peers. To the extent they face more uncertainty, this mechanism is likely to apply to younger firms. A second potential mechanism relates to the existence of import-relevant skills or experience which are not or only partially transferable across workers. Although we do not observe movements of workers in our data, the finding that large firms are more likely to respond to peer activity could reflect poaching of workers with such skills or experience.

Peer characteristics We next examine heterogeneity in peer influence along local peer characteristics. First, we compare the influence of local peers in the industry of the import starter with influence from peers in other industries. We consider two definitions of an industry, using 2-digit and 3-digit categories of the European Union's NACE rev 1.1. classification. Table 12 reveals that the influence from same-sector peers is much stronger. This is true whether we use our discrete (columns 1 and 3) or continuous (columns 2 and 4) measures of peer activity. In the former case, the presence of peers in other sectors importing the same product from the same source country appears to even have a small negative effect on the probability of firms starting to import. For the number of peers the coefficient for other sector peers is positive, but 1-2 orders of magnitude smaller than that of same-sector peers. Results are similar whether we consider 2-digit or 3-digit industries, although coefficients are higher when industries are more narrowly defined.

Second, we examine heterogeneity in peer characteristics such as size, productivity, age and export status. To do so, we group established importers (peers) into quartiles of the distribution of each characteristic. We, then, interact dummies for each quartile with our variable of interest, the lagged number of peers.

Table 11 reports the results. Each column corresponds to a different peer characteristic, and the reference category is the first quartile of each characteristic. Coefficients on the interaction terms reveal that local peer characteristics do indeed affect the extent of peer influence. Our coefficient of interest is systematically higher when local peers are larger (whether measured by employment or sales), more productive (weakly so), have a higher export intensity or are younger. Differences are sizeable relative to the omitted bottom quartile. For instance, the impact of an additional peer is four times larger if this peer is in the 4th quartile of the employment distribution. Heterogeneity in terms of productivity is less systematic and weaker but goes in the same direction. Peer effects are also stronger from firms in the top quartile of the export intensity distribution; and they are strongest from the youngest peers. These results are more suggestive of import starters inferring information from peers' behavior than poaching workers with import-relevant skills, although we cannot formally rule out any of these two alternatives.

Table 11: Peer characteristics

	(1) emp	(2) sales	(3) prod	(4) export int.	(5) firm age
Dep var:			Dummy = 1 if import start		
$NImp_{rpc,t-1}$	.00007	.00007	.00014	.00008	.00019
	(.00001) **	(.00001) **	(.00002) **	(.00001) **	(.00003) **
$\mathbb{1}(Q2) \times NImp_{rpc,t-1}$	.00005				
	(.00001) **				
$\mathbb{1}(Q3) \times NImp_{rpc,t-1}$	.00008				
	(.00002) **				
$\mathbb{1}(Q4) \times NImp_{rpc,t-1}$	.00021				
	(.00004) **				
$\mathbb{1}(Q2) \times NImp_{rpc,t-1}$		.00005			
		(.00001) **			
$\mathbb{1}(Q3) \times NImp_{rpc,t-1}$		.00007			
		(.00002) **			
$\mathbb{1}(Q4) \times NImp_{rpc,t-1}$		.00018			
		(.00003) **			
$\mathbb{1}(Q2) \times NImp_{rpc,t-1}$			.00001		
			(.00001)		
$\mathbb{1}(Q3) \times NImp_{rpc,t-1}$			.00003		
			(.00001) (*)		
$\mathbb{1}(Q4) \times NImp_{rpc,t-1}$			.00003		
			(.00001) *		
$\mathbb{1}(Q2) \times NImp_{rpc,t-1}$				.00012	
				(.00002) **	
$\mathbb{1}(Q3) \times NImp_{rpc,t-1}$				.00010	
				(.00004) **	
$\mathbb{1}(Q4) \times NImp_{rpc,t-1}$				.00017	
				(.00007) *	
$\mathbb{1}(Q2) \times NImp_{rpc,t-1}$					-.00008
					(.00001) **
$\mathbb{1}(Q3) \times NImp_{rpc,t-1}$					-.00008
					(.00001) **
$\mathbb{1}(Q4) \times NImp_{rpc,t-1}$					-.00005
					(.00001) **
constant	.00107	.00108	.00115	.00127	.00108
	(.00006) **	(.00006) **	(.00008) **	(.00008) **	(.00007) **
R^2-adj	.0098	.0097	.0096	.0101	.0095
Obs	71,241,310	71,241,310	64,655,976	54,093,953	70,823,359
mean Dep var	.00151	.00151	.00159	.00174	.00150

Standard errors clustered at CZ level in parentheses. ** p<0.01, * p<0.05, (*) p<0.1. All regressions include country-year, product-year and firm-year fixed effects as well as the respective quartile dummies for each characteristic.

Table 12: Same versus other sector peers

	(1)	(2)	(3)	(4)
Def of sector	Nace 2digit		Nace 3digit	
Dep var:	Dummy = 1 if import start			
$\mathbb{1}(NImp_{\text{same sector}} > 0)_{rpc,t-1}$	.01128		.02278	
	(.00070) **		(.00149) **	
$\mathbb{1}(NImp_{\text{oth sector}} > 0)_{rpc,t-1}$	-.00276		-.00852	
	(.00123) *		(.00230) **	
$NImp_{\text{same sector},rpc,t-1}$		.00106		.00262
		(.00028) **		(.00092) **
$NImp_{\text{oth sector},rpc,t-1}$		.00009		.00011
		(.00001) **		(.00002) **
constant	.00104	.00125	.00119	.00133
	(.00007) **	(.00005) **	(.00005) **	(.00004) **
R^2-adj	.0105	.0105	.0112	.0109
Obs	71,272,152			
mean Dep var	.00151			
country-year FE	yes			
product-year FE	yes			
firm-year FE	yes			

Standard errors clustered at CZ (r) level in parentheses. ** p<0.01, * p<0.05, (*) p<0.1

Table 13: Gravity Interactions

	(1)		(2)		(3)	
Dep var:	Dummy = 1 if import start					
$NImp_{rpc,t-1}$	.00016	(.00003) **	.00015	(.00003) **	.00017	(.00003) **
$NImp_{rpc,t-1} \times CB$	-.00006	(.00001) *				
$NImp_{rpc,t-1} \times CL$			-.00000	(.00001)		
$NImp_{rpc,t-1} \times EEA$					-.00007	(.00001) **
constant	.00112	(.00009) **	.00107	(.00008) **	.00115	(.00009) **
R^2-adj	.0095		.0095		.0095	
Obs	71,272,152					
mean Dep var	.00151					
country-year FE	yes					
product-year FE	yes					
firm-year FE	yes					

Standard errors clustered at CZ level in parentheses. ** p<0.01, * p<0.05, (*) p<0.1
CB = Common Border, CL = Common Language, EEA = European Economic Area.

Finally, we explore heterogeneity across countries in peer influence to shed more light on mechanisms. First, we interact our variable our interest with ‘gravity’ variables such as having a common border (CB), a common language (CL) or belonging to the European Economic Area (EEA, an economic zone with provisions beyond a free trade agreement). Table 13 shows that existing importers from countries that share a border with France or belong to the EEA exhibit less peer influence. Coefficients of the variable of interest are almost halved relative to the baseline. Instead, imports from French-speaking countries (Belgium and Switzerland in our sample) do not exhibit different patterns of peer influence. These results are consistent with an explanation where imports starters observe their peers in order to overcome informational barriers to trade, which are likely higher in non-neighboring countries and countries outside the EEA.

In sum, our results provide evidence of robust and substantial peer effects in firm's decisions to import, even when controlling for zone-time or industry-time unobservables. These effects are stronger within the same sector, and do not come from intra-firm or intra-group coordination. They are stronger among large, among young firms, and among exporters. The preceding lines of investigation do not allow us to attribute the peer effects to either pure (observational) learning or knowledge transmission through interaction or worker mobility. Chances are that the measured effects are a combination of both. The survey information used by Foster and Rosenzweig (1995) in their paper on the role of learning in adoption of new seed varieties suggests that both information and neighbors matter.

We rely on within firm-year variation in the number of peers for identification. While we believe that this specification addresses many concerns with potential omitted variable bias, we cannot go as far as claiming causality. Therefore, we complement this analysis by examining the consequences of being close to many versus few peers on the number of import starters in a commuting zone following a period of trade liberalisation. Exploiting an arguably exogenous policy shock allows us to examine the causal impact of importing peers more closely.

4 Commuting zone-level exercise

Aggregating to the commuting zone level, the policy episode we look at is the elimination of import quotas prescribed by the Multi-Fibre Arrangement. We begin by laying out the estimation strategy before describing this trade policy episode in more detail. Here we use a difference-in-difference (DD) approach:

$$NImpStart_{rpct} = \beta D_{rpc} \cdot postLIB_{pct} + \gamma D_{rpc} + \delta postLIB_{pct} + \lambda_{rpc} + \varepsilon_{rpct}, \tag{3}$$

where the dependent variable, $NImpStart_{rpct}$, is the number of firms located in CZ r that start importing product p from country c in year t. We consider a firm as treated if: $D_{rpc} \cdot postLIB_{(pc)t} =$

1. D_{rpc} takes value 1 if a commuting zone falls into the top quartile according to the number of firms importing product p from country c four or five years before trade liberalisation, 0 otherwise. In other words, for the purpose of this exercise, we associate peer effects with the presence of many versus few existing importers of the same product from the same source country in the same commuting zone. $postLIB_{pct}$ is a dummy variable equal to 1 from the year of trade liberalisation onward and 0 otherwise. We include CZ-product-source country fixed effects λ_{rpc} in this regression. These capture everything that is specific to the commuting zone-product-source country triplet over time, and thus, for example, reasons why certain commuting zones will be more prone to importing (certain products from certain countries).

As we have a count dependent variable, we estimate equation (3) using a fully flexible fixed effects Poisson (FEP) quasi-maximum likelihood regression proposed for nonlinear dependent variables by Wooldridge (2021). The specification is as follows:

$$E(y_{it}|d_{iq},\ldots,d_{iT}) = c_i exp\left[\sum_{s=2}^{T}\theta_s fs_t + \sum_{r=q}^{T}\sum_{s=r}^{T}\tau_{rs}(w_{it}\cdot d_{ir}\cdot fs_t),\right] \tag{4}$$

where y_{it} is the outcome variable. $\{fs_t : t = 2,\ldots,T\}$ with $fs_t = 1$ if $s = t, fs_t = 0$ if $s \neq t$ are time-specific effects (year dummies in the present setting); fs_1 is redundant and can be dropped. The time-varying treatment indicator is defined as $w_{it} = d_i \cdot p_t$, where d_i is a dummy variable equal to 1 if unit i is eventually treated and p_t is the dummy variable indicating the post-treatment time periods: $p_t = 0, t = 1,\ldots,q-1$, and $p_t = 1, t = q,\ldots,T$. Crucially, from $t = q$, some units are subject to an intervention. c_i captures unit heterogeneity. The FEP estimator is fully robust to distributional misspecification and serial dependence. Because of the exponential functional form, τ_{rs} is (approximately) a proportionate effect.

The common or parallel trends assumption imposed in this instance requires that for a known, strictly increasing, continuously differentiable function $G(\cdot)$ and parameters α, β, and $\gamma_2,\ldots,\gamma_T$,

$$E[y_t(0)|d] = G(\alpha + \beta d + \gamma_t), t = 1,2,\ldots,T \quad (\gamma_1 \equiv 0)$$

or equivalently,

$$G^{-1}(E[Y_t(0)|d]) - G^{-1}(E[Y_{t-1}(0)|d]) = \gamma_t - \gamma_{t-1}, t = 2,\ldots,T.$$

Note the transformation of the mean does not depend on d.

We use this methodology to assess the differential impact in commuting zones with many established importers relative to commuting zones with few established importers on the number of import starters as a consequence of the removal of import quotas for CN8 digit clothes & textile products by the EU to comply with the Multifibre Arrangement in three waves, 1998, 2002 and 2005.

Table 14: Number of CN8 products subject to MFA quota eliminations

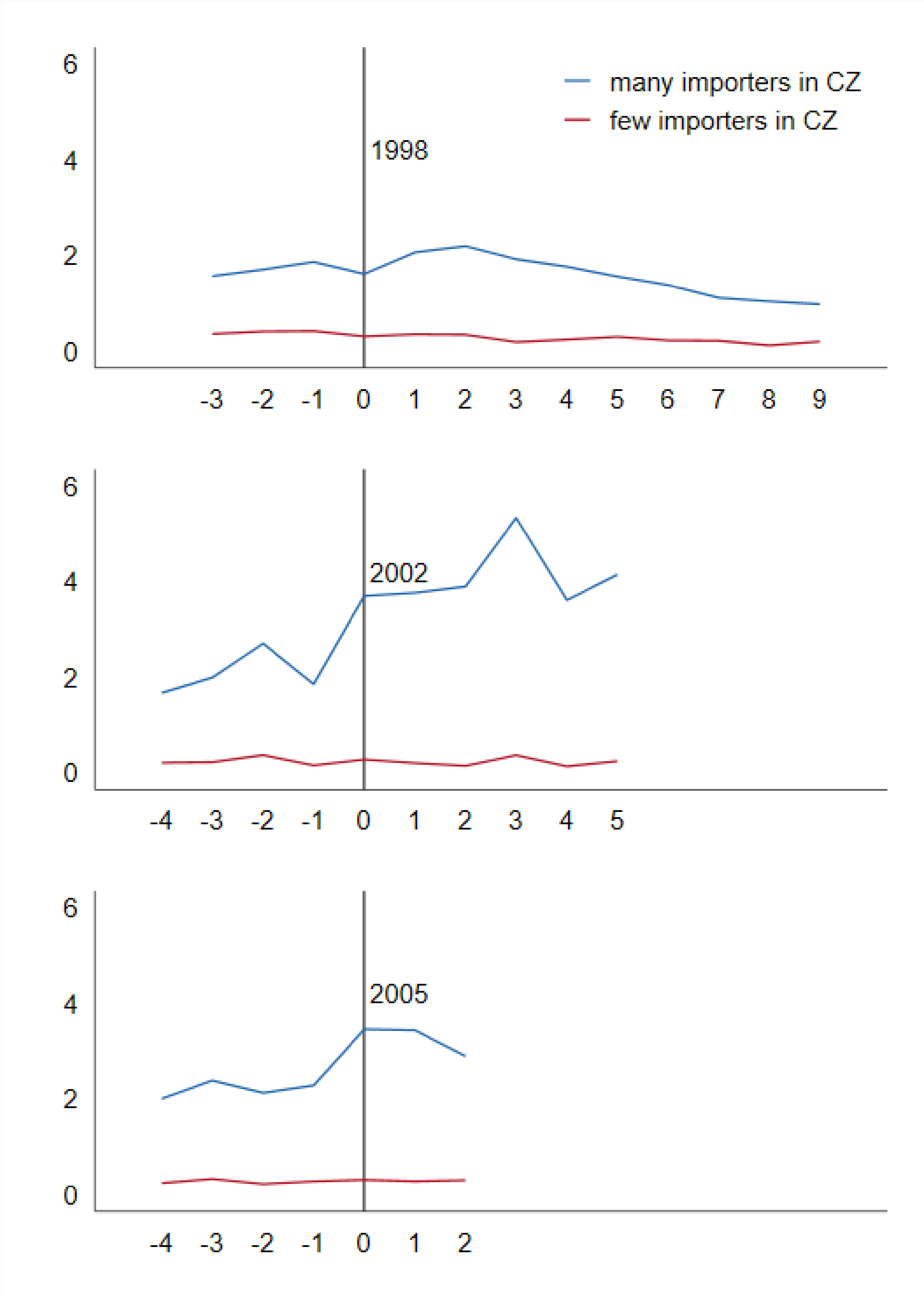
MFA phase	at EU level[1]	imported by France	sample[2]
1998	3039	778	92
2002	1045	561	44
2005	4737	2131	203

[1] From the European Commission's SIGL database.
[2] To be included in the sample the product needs to have been imported to France from a quota country by importers in 1994 for the 1998 cohort, in 1997 for the 2002 cohort, and in 2000 for the 2005 cohort. There also needs to be sufficient variation in the number of importers of a product across commuting zones for the above and below p75 split to be defined.

Trade in textiles and clothing was excluded from the General Agreement on Tariffs and Trade (GATT) when it was signed in 1948. The MFA was established based on predecessors that covered only a subset of fibres (mostly cotton) in 1974. It allowed the developed countries to protect their textile and clothing industries by imposing import quotas for clothes and textile products from developing countries. The Uruguay round of the GATT came to the Agreement on Textiles and Clothing (ATC) that replaced the MFA in 1995. The ATC foresaw the phased elimination of MFA quotas in January of 1995, 1998, 2002, 2005. Quotas were to be eliminated, equivalent to 16 percent of 1990 imports at the beginning of 1995, 17 percent at the beginning of 1998, 18 percent at the beginning of 2002, and the remaining 49 percent at the beginning of 2005. It was up to the imposing countries to decide on the products to be included in each phase. Unsurprisingly the EU and the other developed countries left the removal of quotas for the products that affected their producers most until the last phase in 2005. As our sample period is 1994-2007, our analysis covers the last three rounds of quota abolition in 1998, 2002 and 2005. Referring back to equation (3), we consider a product as treated ($postLIB_{p(c)t} = 1$) from the year the EU abolished the quota.

Our sample in this instance covers the subset of CN8 textile and clothing products (HS chapters 50-67) that were subject to quota abolition by the EU and that were imported by France five years before quota removal (four years in the case of the 1998 cohort, as 1994 is the first year in our sample period. We split commuting zones into many versus few peer zones (D_{rpc}) at the 75th

Figure 2: MFA: Trends in the number of import starters in CZs by MFA cohort



Note: Figure plots the number of import starters in commuting zones with many and few importers five years before the respective year of quota removal (four years for the 1998 cohort).
Many - blue line: CZ is in the top quartile according to the number of importers by product and source country.
Few - red line: CZ is in one of the bottom three quartiles according to the number of importers by product and source country.

percentile of the distribution of the number of importers of the same CN8 product from the source country five years before the year the quota was removed (again four years before in case of the 1998 cohort). Table 14 shows the number of potentially treated products at EU level for each of the three cohorts, the subset of these imported to France, and the number of those we are able to use for the difference-in-difference analysis based on our sample split.[20] Our sample covers about 10 percent of products imported by France that had quotas removed in each phase.

As a product-country specific quota is removed only once, we treat the three phases as strand-alone exercises and run three separate fixed effects Poisson Maximum Likelihood regressions as set out in equation (4). The regressions include commuting zone-country-CN8 product fixed effects. We cluster standard errors at the commuting zone level as there may be several country-product combinations subject to quota removal in a commuting zone.

Figure 2 plots the average number of import starters in commuting zones with many versus few importers of the same product from the same country around the time of quota removal for the 1998, 2002 and 2005 cohorts. On visual inspection pre-trends appear reasonably parallel for all three phases. We test for this formally below in the regression framework.

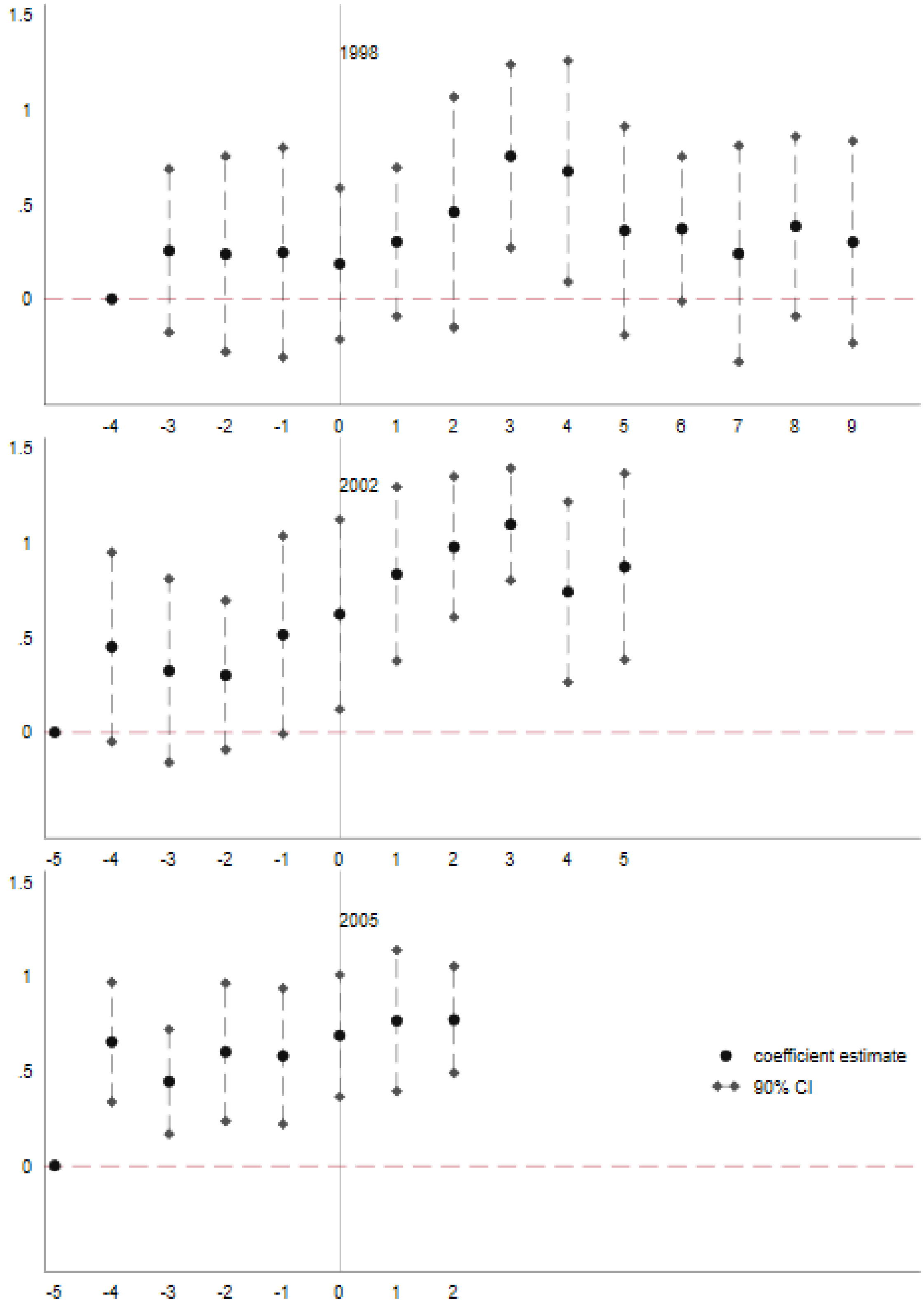
Figure 3 presents the coefficient estimates and 90 percent confidence intervals for the probability of starting to import following the MFA quota eliminations based on estimating equation (4). Table 15 reports full estimation results for each of the three cohorts individually.

The coefficient estimates for all three phases indicate that there is an increase in the probability to start importing following quota abolition in commuting zones with many versus few established importers of the same product from the same country. The response is somewhat sluggish following the first phase in 1998, the coefficients become large and statistically significant starting four years after quota elimination. For the 2002 and 2005 phases, the impact is immediate and quite large: the number import starters in zones with many established peers is 60-110 higher compared to zones with few peers. The cohort average effects are in the region of 85 and 75 percent for the 2002 and 2005 phases. The χ^2-test for parallel pre-trends fails to reject the null that the coefficient estimates for the periods prior to the tariff reductions are jointly significant for the 1998 and 2002 phases, but not for the 2005 phase.

The lack of parallel trends for the 2005 cohort might be related to China's WTO accession in late 2001, which removed quotas on some MFA products and reduced tariffs to MFN levels on many

[20] The set of countries that benefited from quota removal in the estimation sample is: Argentina, Hungary, Morocco, Poland, Romania, Russian Federation in 1998; Brazil, China, Hong Kong, India, Korea, Thailand, Taiwan in 2002; China, Hong Kong, Indonesia, India, Korea, Macao, Philippines, Pakistan, Thailand, Taiwan, Vietnam in 2005. China only entered the WTO in 2001, thus it did not benefit from the first two phases of quota removal.

Figure 3: MFA: Estimated coefficients by MFA cohorts



Note: Figure plots the estimated coefficients from equation (4).

Table 15: MFA: regression results

	(1)		(2)		(3)		(4)	
Cohort	1998		2002		2005		2005 excl. China	
Dep var:	N import starters by rpc and year							
coh1998 × 1998	0.186	(0.243)						
coh1998 × 1999	0.303	(0.239)						
coh1998 × 2000	0.458	(0.370)						
coh1998 × 2001	0.755	(0.294) *						
coh1998 × 2002	0.675	(0.354) (*)						
coh1998 × 2003	0.361	(0.335)						
coh1998 × 2004	0.370	(0.232)						
coh1998 × 2005	0.240	(0.348)						
coh1998 × 2006	0.384	(0.288)						
coh1998 × 2007	0.301	(0.324)						
coh2002 × 2002			0.623	(0.304) *				
coh2002 × 2003			0.836	(0.279) **				
coh2002 × 2004			0.980	(0.225) **				
coh2002 × 2005			1.098	(0.180) **				
coh2002 × 2006			0.741	(0.289) *				
coh2002 × 2007			0.875	(0.299) **				
coh2005 × 2005					0.687	(0.196) **	0.362	(0.196) (*)
coh2005 × 2006					0.766	(0.227) **	0.407	(0.294)
coh2005 × 2007					0.772	(0.171) **	0.390	(0.213) (*)
coh2005 × 2001					0.654	(0.192) **	0.473	(0.204) *
Wald χ^2 (p)	36834.4	(0.00)	2464544.8	(0.00)	5503.5	(0.00)	3772.3	(0.00)
N	3806		1677		5157		3455	
cohort avg (SE)	0.403	(0.255)	0.859	(0.216)	0.741	(0.185)	0.386	(0.210)
Pretrends								
coh1998 × 1995	0.256	(0.262)						
coh1998 × 1996	0.237	(0.314)						
coh1998 × 1997	0.247	(0.337)						
coh2002 × 1998			0.451	(0.304)				
coh2002 × 1999			0.326	(0.295)				
coh2002 × 2000			0.302	(0.239)				
coh2002 × 2001			0.515	(0.318)				
coh2005 × 2002					0.444	(0.168) **	0.386	(0.193) *
coh2005 × 2003					0.601	(0.221) **	0.551	(0.275) *
coh2005 × 2004					0.579	(0.218) **	0.346	(0.257)
χ^2 (p)	0.960	(0.811)	3.737	(0.443)	11.824	(0.019)	6.842	(0.144)

FE Poisson MLE estimation with country-product-commuting zone fixed effects. Year dummies included in all regressions.

Standard errors adjusted for clustering at the CZ level in parentheses. ** p<0.01, * p<0.05, (*) p<0.1.

non-MFA products.[21] For this reason we report the results for the 2005 cohort excluding China in the last column of Table 15. While two of the coefficients pre-treatment are still significant, the χ^2-test fails to reject the null that the coefficients for the three pre-periods jointly are significant suggesting that the parallel trends assumption is viable. Also with China excluded, the removal of quotas in the last round had a significant impact on the number of import starters after 2005. The cohort average effect suggests that the number of import starter is 38 percent higher in zones with many established peers compared to zones with fewer peers. Note that both in the 2002 and 2005 cohorts the effects persist until the end of the sample period.

We take this as complementary evidence of peer effects. This exercise relies on a different source of variation in the data and is yet supportive of our hypothesis that being in close proximity to a larger number of established importers of the same product from the same country increases the probability of additional firms to start importing.

5 Conclusion

In this paper we examine the hypothesis that firms starting to import are influenced by local peer importing activity. Using a rich dataset on imports of French firms between 1997 and 2007, we find that firms are more likely to start importing in the presence of local peers that import or started to import recently. This conclusion is supported by different sources of variation in the data. First, we estimate positive spillover effects at firm level in a sample that spans various products and countries. In our preferred specification, we find that being located near peers that imported the same product from the same country more than doubles the baseline probability of starting to import. Second, we also find evidence of positive spillovers in a setting with an exogenous trade policy shock, namely the effect of the elimination of clothing & textile quotas established under the Multi-Fibre Arrangement. Our method relies on comparing the number of import starter in commuting zones with many existing importers to commuting zones with few. In this exercise, we find that following MFA quota elimination the number of import starters is on average between 40 and 90 percent higher in zones with many relative to zones with few peers.

We find that a) larger as well as younger firms benefit more from spillovers and b) same sector, larger, younger peers as well as exporters are greater sources of spillovers. This is consistent with pure (observational) learning or exchanges between firms that transmit information possibly through labor mobility or a combination of both.

[21] Complementarities between those products and yet-to-be-treated MFA products, for example in import demand or in transport costs, would imply more import starts in the treatment group *before* 2005.

Our results show economically significant effects, that echo the export spillovers found in the literature. As with exports, this implies that the social returns to *importing* exceed the private return. While a welfare analysis of import subsidies is beyond the scope of this paper, our results suggest that non-distortionary import promotion policies are desirable. While government support for trading firms typically focuses on exporters, China's recent initiative to organize an annual International Import Expo provides an example of such import-promotion policies. Evaluating the impact of such measures on the extensive margin of imports would be an interesting avenue for future research.

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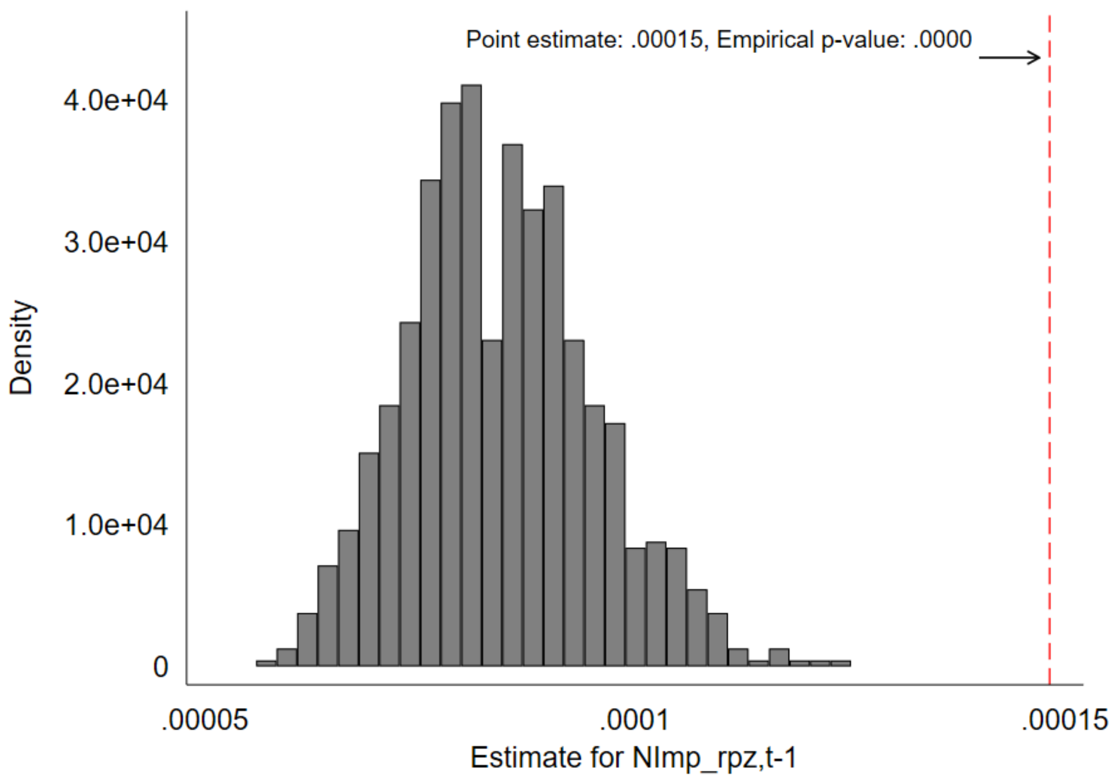
A Appendix

Table A1: Shares of importers and import starters

	(1)	(2)	(3)	(4)
	Importer peers		Import starter peers	
Dep var:	Dummy = 1 if import start			
$\frac{NImp_{rpc,t-1}}{Nfirms_{r,t-1}}$	5.411	7.390		
	(0.545) **	(0.664) **		
$\left(\frac{NImp_{rpc,t-1}}{Nfirms_{r,t-1}}\right)^2$		-358.012		
		(70.077) **		
$\frac{NImpStarter_{rpc,t-1}}{Nfirms_{r,t-1}}$			13.965	16.781
			(1.325) **	(1.686) **
$\left(\frac{NImpStarter_{rpc,t-1}}{Nfirms_{r,t-1}}\right)^2$				-1689.825
				(476.992) **
constant	0.0010	0.0008	0.0011	0.0010
	(0.0001) **	(0.0001) **	(0.0000) **	(0.0000) **
R^2-adj	0.0102	0.0104	0.0100	0.0101
Obs	71,272,152			
mean Dep var	.00151			
country-year FE	yes			
product-year FE	yes			
firm-year FE	yes			

Standard errors clustered at CZ (r) level in parentheses. ** p<0.01, * p<0.05, (*) p<0.1

Figure A1: Randomization inference



Note: Distribution of coefficient estimates obtained by re-estimating equation (1) with random reassignment of the number of source country-product peers across commuting zones within year 1,000 times.

Table A2: Robustness

	(1) baseline	(2) second lag	(3) add WS&Ret peers	(4) excl. Paris	(5) excl. 3dig sector cells never imported from
Dep var:			Dummy = 1 if import start		
$NImp_{rpc,t-1}$	.00015		.00014	.00021	.00015
	(.00003) **		(.00002) **	(.00005) **	(.00003) **
$NImp_{rpc,t-2}$		.00015			
		(.00003) **			
$NImpWsRet_{rpc,t-1}$			.00001		
			(.00001)		
constant	.00108	.00071	.00106	.00113	.00123
	(.00007) **	(.00008) **	(.00008) **	(.00010) **	(.00008) **
R^2-adj	.0095	.0103	.0095	.0092	.0105
Obs	71,272,152	61,597,764	71,272,152	63,729,486	62,629,881
mean Dep var	.00151	.00116	.00151	.00152	.00171
country-year FE			yes		
product-year FE			yes		
firm-year FE			yes		

Standard errors clustered at CZ level in parentheses. ** p<0.01, * p<0.05, (*) p<0.1

Table A3: Import starter characteristics, by quartile

	(1)	(2)	(3)	(4)	(5)
	emp	sales	prod	export share	firm age
Dep var:			Dummy = 1 if import start		
$NImp_{rpc,t-1}$	.00007	.00007	.00014	.00008	.00019
	(.00001) **	(.00001) **	(.00002) **	(.00001) **	(.00003) **
$\mathbb{1}(Q2) \times NImp_{rpc,t-1}$	.00005				
	(.00001) **				
$\mathbb{1}(Q3) \times NImp_{rpc,t-1}$	.00008				
	(.00002) **				
$\mathbb{1}(Q4) \times NImp_{rpc,t-1}$	.00021				
	(.00004) **				
$\mathbb{1}(Q2) \times NImp_{rpc,t-1}$		.00005			
		(.00001) **			
$\mathbb{1}(Q3) \times NImp_{rpc,t-1}$		.00007			
		(.00002) **			
$\mathbb{1}(Q4) \times NImp_{rpc,t-1}$		.00018			
		(.00003) **			
$\mathbb{1}(Q2) \times NImp_{rpc,t-1}$			.00001		
			(.00001)		
$\mathbb{1}(Q3) \times NImp_{rpc,t-1}$			.00003		
			(.00001) (*)		
$\mathbb{1}(Q4) \times NImp_{rpc,t-1}$			.00003		
			(.00001) *		
$\mathbb{1}(Q2) \times NImp_{rpc,t-1}$				.00012	
				(.00002) **	
$\mathbb{1}(Q3) \times NImp_{rpc,t-1}$				.00010	
				(.00004) **	
$\mathbb{1}(Q4) \times NImp_{rpc,t-1}$				.00017	
				(.00007) *	
$\mathbb{1}(Q2) \times NImp_{rpc,t-1}$					-.00008
					(.00001) **
$\mathbb{1}(Q3) \times NImp_{rpc,t-1}$					-.00008
					(.00001) **
$\mathbb{1}(Q4) \times NImp_{rpc,t-1}$					-.00005
					(.00001) **
constant	.00107	.00108	.00115	.00127	.00108
	(.00006) **	(.00006) **	(.00008) **	(.00008) **	(.00007) **
R^2-adj	.0098	.0097	.0096	.0101	.0095
Obs	71,241,310	71,241,310	64,655,976	54,093,953	70,823,359
mean Dep var	.00151	.00151	.00160	.00174	.00150
country-year FE			yes		
product-year FE			yes		
firm-year FE			yes		

Standard errors clustered at CZ level in parentheses. ** p<0.01, * p<0.05, (*) p<0.1