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New Imported Inputs, New Domestic Products

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Abstract

We study the effects of new imported inputs on the entry of new domestic products and their characteristics. To this purpose, we construct a novel, comprehensive and extremely detailed dataset, which contains product-level information on foreign trade and domestic production for 25 EU countries over 1995-2007. Using these data, we identify new domestic goods and new imported inputs, controlling for all changes in commodity classifications over time. We then show that new imported inputs substantially boost the introduction of new domestic products. We also show that this effect is directly proportional to the quality of new imported inputs and inversely related to their price (conditional on quality). Finally, we document that new products are characterized by higher prices and higher quality relative to existing goods, and that such premia are larger the greater is the use of new imported inputs in production.

JEL codes: F1.

Keywords: New Intermediate Inputs; Product Innovation; Input and Output Prices; Input and Output Quality; Product-Level Data.

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1 Introduction

New products matter for economic growth. This is one of the key messages of the endogenous growth theory, which has long identified the introduction of new and upgraded goods as a crucial driver of growth.[1] Several theoretical contributions have highlighted that new imported inputs help countries introduce new goods, by reducing the cost of innovation and relaxing technological constraints.[2] In recent decades, world trade has increasingly involved intermediate inputs, and countries have gained access to a growing number of *new* foreign intermediates.[3] Surprisingly, though, empirical evidence on the link between new imported inputs and new domestic products has been lacking. Recently, Goldberg et al. (2010a) have shown that new imported inputs have contributed to the expansion of firms' product scope in India over the 1990s. Building on their work, this paper shows that new imported inputs are also a crucial driver of product innovation, measured at the economy-wide level, in the industrialized world.

We focus on 25 EU countries over 1995-2007, and assess how new imported inputs affect the entry of new domestic products and their characteristics. Our analysis proceeds in three phases. First, we study whether new imported inputs have an impact on the introduction of new goods. Second, we analyze the channels through which this effect occurs, by emphasizing three possible drivers: number, price and quality of new imported inputs. Finally, we investigate how new goods differ from the existing ones, in terms of volumes, prices and quality, and how such differences depend on the use of new imported inputs in production.

Our analysis rests on the most comprehensive and detailed data on foreign trade and domestic production available for the EU. As explained in Section (2), we draw production data from the Prodcom database (Eurostat), which contains yearly information on the value and volume of domestic production for all 8-digit products in all EU countries. As for trade data, we use the Comext database (Eurostat), which contains yearly information on the value and volume of trade (imports and exports) for all 8-digit products and all trading partners in the world. The first task we ac-

[1] See, in particular, Segerstrom et al. (1990), Grossman and Helpman (1991a,b), Aghion and Howitt (1992), Romer (1994) and Segerstrom (1998).

[2] See Ethier (1979, 1982), Romer (1987, 1990), Markusen (1989), Grossman and Helpman (1990) and Rivera-Batiz and Romer (1991).

[3] For the importance of intermediate inputs in world trade, see Feenstra (1998) and Yi (2003). Goldberg et al. (2009) discuss the role of new inputs in the growth of intermediate imports, focusing on India. More in general, Broda and Weinstein (2006), Broda et al. (2006), Bernard et al. (2009) and Kehoe and Ruhl (2009) highlight the role of new goods in overall trade growth.

complish is to identify new domestic products and new imported inputs. Throughout the paper, we define them as follows. A product is new for a country when the first domestic firm starts producing it, and thus a positive production is recorded in Prodcom. Similarly, a new foreign intermediate is an input that is imported from a certain trading partner for the first time.[4] Identifying new domestic products and new imported inputs is not trivial, because the commodity classifications change every year following the EU legislation. To address this issue, we keep track of all the classification changes occurring over the sample period, by using the year-to-year correspondence tables provided by Eurostat.

Before starting the econometric analysis, we provide evidence on the quantitative relevance of new domestic products and new imported inputs for our countries. We show that new products represent a non-negligible share of all domestic goods (5% per year, on average), and account for a substantial share of manufacturing output growth (25% per year, on average). The picture for imports is similar. In fact, new intermediates represent 13% of all input varieties imported each year, and account for 20% of growth in the value of imported inputs.

Next, we turn to the econometric analysis. In Section (3), we investigate whether new imported inputs have an impact on the introduction of new goods. For each country, industry and year, we compute the share of new domestic products in the total number of domestic products, and regress it on the (lagged) share of new imported inputs in the total number of imported inputs. In order to accommodate backward linkages across industries, we weight the latter variable with country-specific Input-Output coefficients. We find that new imported inputs bolster the introduction of new domestic goods. In particular, our preferred specification implies that a 1 percentage-point increase in the share of new imported inputs is associated with a 0.57 percentage-point increase in the share of new domestic goods. According to a simple back-of-the-envelope calculation, this implies that new imported inputs explain one-fourth of the average contribution of new goods to output growth.

This result proves strikingly robust across a large number of alternative specifications. In particular, we show that it holds unaffected when we: account for outliers; address potential issues with our regressor and dependent variable; use values instead of numbers to construct them; control for

[4] Following the empirical literature, we work under the standard assumption that each product-partner combination (variety) is a different good. See, e.g., Hummels and Klenow (2005) and Broda and Weinstein (2006). For applications of this definition to imported intermediates, see Goldberg et al. (2009, 2010a).

a wide set of phenomena related to globalization and technological change; and employ longer lags of the regressor in the specification. In addition, we find that the effect of new imported inputs is somewhat stronger for New EU Members, and for imported inputs from OECD countries.

We also use two different approaches to tackle the potential endogeneity of new imported inputs, and to make sure that their effect is properly identified. First, we run Instrumental Variables regressions using different sets of instruments, which are meant to capture the fraction of variation in new imported inputs that is exogenous to product innovation. In particular, our preferred instruments are long lags of imported inputs and input tariffs in the US. Second, we pick up this exogenous variation by exploiting a series of trade shocks occurred over the sample period. In particular, we consider shocks to some of the countries in our sample (adoption of the Euro and accession to the EU), to some of their trading partners (accession to the WTO), and to some of the inputs sourced from abroad (extreme changes in tariff levels). All these identification exercises confirm, and possibly reinforce, our baseline result: new imported inputs stimulate domestic product innovation.

In Section (4), we study the channels through which this effect occurs. Following the relevant empirical work in this area, and in particular Goldberg et al. (2010a) and Kugler and Verhoogen (2009), we jointly investigate three possible mechanisms: (1) expansion in the number of available intermediates, which allows producing new goods in the presence of essential inputs; (2) access to cheaper inputs, which makes it profitable to produce goods otherwise too costly; (3) access to higher quality inputs, which renders the manufacturing of some products technologically feasible. As a first step, we add to our baseline specification an interaction term between the share of new imported inputs and their relative price (expressed in terms of other imported inputs). This variable has a positive and significant coefficient. If higher input prices are a signal of higher input quality, as argued by Kugler and Verhoogen (2009), this result suggests that the effect of new imported inputs may be stronger the higher is their relative quality. In order to explore this issue, we construct time varying estimates of quality for all imported input varieties, by applying the methodology developed by Khandelwal (2010) to all of the countries in our sample. Using these quality estimates we further extend the specification, by interacting the share of new imported inputs with their relative quality. We find robust evidence that the effect of new imported inputs becomes stronger as their quality increases. Interestingly, the coefficient of the price interaction turns negative once conditioning on quality. This suggests that, at given quality, the effect of new imported inputs is stronger the lower their price. We view these two results as consistent with the second and third mechanisms mentioned above. Instead, we do not find any evidence in favor of the first mechanism. In our specifications, the latter is captured by the linear coefficient of the share of new imported inputs, which is generally small and imprecisely estimated.

Finally, in Section (5) we unveil differences between new and existing goods in terms of volumes, prices and quality, and study how such differences depend on new imported inputs. In this part of the analysis we work at the product level, instead of aggregating the data at the industry level. We first show that new domestic products are sold in smaller volumes, but at higher prices, relative to existing goods. We document that the price premium is larger the more the industry relies on new imported inputs, whereas the quantity difference is not influenced by the use of new foreign intermediates. Next, we ask how consumers perceive the quality of new products relative to that of existing goods, and how the difference depends on the use of new imported inputs in production. To investigate this issue, we construct data on new exported goods to the US, and match them with Khandelwal's (2010) quality estimates for US imports. We find that new EU exports to the US display a substantial quality premium relative to existing exports, and that this quality premium grows stronger the more production (in the EU) relies on new imported inputs.

As already mentioned, our analysis is inspired by Goldberg et al. (2010a), which provides the only direct evidence to date on the link between new imported inputs and domestic product innovation. Using India's trade liberalization in the 1990s as an exogenous trade shock, the authors identify a large positive effect of new imported inputs on firms' product scope. Our paper differs from theirs in three respects. First, we consider a large group of industrialized countries, rather than a fast-growing developing economy. Second, we focus on country-level, as opposed to firm-level, product innovation; this difference may be relevant inasmuch as products that are new for a firm may not be new for the country as a whole. Third, and most importantly, we analyze the mechanisms through which new imported inputs operate, as well as the main differences between new and existing goods.

Apart from Goldberg et al. (2010a), evidence on the link between new imported inputs and new domestic products has been lacking. The main reason is the unavailability of detailed data on domestic production. In a different context, some studies have used data on exported goods as a proxy.[5] However, new exported goods are an imperfect proxy for new domestic products, as many of the latter may be sold only in the domestic market, at least in an early phase. To the best of our knowledge, we are the first to employ data on domestic production for the universe of manufacturing goods, across many countries and many years.

Our results are also complementary to the recent studies on the characteristics of new goods, and in particular to Broda and Weinstein (2010) and Xiang (2005). Using bar-code data for the US, Broda and Weinstein (2010) show that the higher quality of new goods accounts for a substantial fraction of the increase in the consumer price index. While bar-code data are extremely well suited to identify new consumption patterns, they are perhaps less suitable than our data to capture product innovation, which is the main focus of this paper. Xiang (2005) shows that production of new goods requires higher technology- and skill-intensity, which tend to be associated with higher output quality (see, in particular, Verhoogen, 2008). Compared to Xiang's study, we are able to identify new products on a yearly basis, rather than between two single points in time.[6] Moreover, we observe the value and volume of production, which allows us to compare new and existing goods along several important dimensions.

Finally, the paper is related to two other streams of empirical literature. The first explores the effect of imported inputs on domestic productivity. With a few exceptions, the existing studies show that imported inputs have a positive, and generally sizeable, productivity effect.[7] In the endogenous growth theory (e.g., Rivera-Batiz and Romer,1991), such a productivity effect is referred to as the "level effect" or "static gain", and is one of the factors behind the introduction of new products, the so-called "growth effect" or "dynamic gain". The latter effect has been largely overlooked in the empirical literature, and constitutes the focus of this paper. The second stream of literature deals with the welfare implications of new imported varieties. With a few exceptions, the existing studies show that new foreign varieties bring about substantial welfare gains.[8] Our analysis complements also these studies, by bringing to light the desirable effects of new imported inputs on product innovation.

[5] See, e.g., Feenstra et al. (1999) and Broda et al. (2006).

[6] In brief, Xiang compares the SIC72 and the SIC87 classifications, and defines as new the products that are absent in the former but present in the latter classification.

[7] See, among others, Amiti and Konings (2007), Kasahara and Rodrigue (2008), Halpern et al. (2009), Sivadasan (2009) and Khandelwal and Topalova (2011). See Muendler (2004) for a notable exception.

[8] See Feenstra et al. (1992), Feenstra (1994), Broda and Weinstein (2006) and Broda et al. (2006). See Arkolakis et al. (2008) for a notable exception.

2 Data and Stylized Facts

2.1 Data

Data on domestic production are sourced from the Eurostat Prodcom (PC) Database. The latter contains yearly information on the value and volume of sold production, for individual products, in all EU countries except Cyprus and Malta.[9] PC is based on an extensive yearly survey of the production activities carried out by firms within the territory of each reporting country.[10] This survey covers the entire manufacturing sector, i.e., Section D of the NACE Rev. 1.1 classification. According to the EU regulation, the PC survey must cover at least 90% of production in each 4-digit NACE industry, in each country.[11] The PC classification contains about 4,500 8-digit product codes and is directly linked to the NACE classification: the first four digits of the PC code identify the 4-digit NACE industry. This enables us to easily map products into industries. The PC data are available since 1995, with some differences across countries (see Table A2). The PC classification has been completely restructured in 2008, following the shift from NACE Rev. 1.1 to NACE Rev. 2. A complete correspondence between these two classifications cannot be produced, so our analysis stops in 2007.

A crucial task for our study is to identify new products. We define a product as new for a country when the first domestic firm starts producing it, and thus a positive production is recorded in PC. The identification of new products is dramatically complicated by the fact that the PC classification changes every year, following the EU legislation. As standard for product classifications, the changes are mainly of two types: (1) new products are added to the classification, with new codes; and (2) some of the existing ("old") product codes are converted into a new product code. This second change is problematic for our purposes, as it reflects renaming of products rather than true product entry. To identify these cases, we employ the year-to-year correspondence tables provided

[9] We thus focus on 25 rather than 27 EU Members. Note that Belgium and Luxemburg are aggregated by Eurostat, and thus constitute a single unit of analysis.

[10] PC does not cover the production activities undertaken outside the national borders, e.g., in foreign subsidiaries of domestic multinationals.

[11] For the period under analysis (1995-2007), the following categories of firms were required to report data on their production activities: (1) firms with a primary manufacturing activity and at least 10 employees; (2) firms with a primary manufacturing activity and less than 10 employees, with turnover above a minimum threshold; (3) firms with a non-manufacturing primary activity and at least 20 employees; (4) firms with a non-manufacturing primary activity and less than 20 employees, with turnover above a minimum threshold. The inclusion criteria have changed in 2008; see Bernard, Van Beveren and Vandenbussche (2010) for a discussion.

by Eurostat. As a result, when a new code appears in the classification, we know exactly whether it represents a new product or is just a new indicator for one or more existing products. Taking this into account, we then identify code p, produced by country c in year t, as a new product if either: (1) the code is introduced in the classification in year t and does not have any old corresponding code; or (2) the code is introduced in the classification in year t and has one or more old corresponding codes, but none of the latter was ever produced by country c before (i.e., since the first available year in our sample); or (3) the code is not new to the classification, but was never produced before by country c. We use a mirror-like strategy to identify exiting products. Importantly, this identification routine implies that a product can be counted as new, or exiting, only once: if production stops and resumes later on, we do not count this as exit and entry. Hence, in our data, product entry and exit are not spuriously driven by classification changes, nor do they reflect discontinuities in production over time.

Examples of new products for some of the countries in our sample are as follows. Spain started producing "Flat panel video monitors, LDC or plasma" (PC code 32302049) in the year 2000. In previous years, that country already produced "Color video monitors with cathode-ray tube" (PC code 32302045). The Netherlands started producing "Photocopiers incorporating an optical system" (PC code 30012185) in the year 2002. In previous years, that country already produced "Electrostatic photocopiers" (PC code 30012170).

Turning to the international trade data, we source them from the Eurostat Comext database. For all EU countries, the latter contains yearly information on the value and volume of trade (imports and exports) for all products and trading partners in the world (about 200 partners). Data are available since 1988, with some differences across the EU countries (see Table A2). Products are classified according to the Combined Nomenclature (CN) classification, which contains more than 10,000 8-digit product codes. The CN classification can be linked to the NACE classification through appropriate correspondence tables provided by Eurostat. We also map the CN classification into the Broad Economic Categories (BEC) classification, so as to identify the intermediate inputs.[12]

[12] In particular, intermediate inputs are all CN codes mapped into the following BEC categories: Processed food and beverages, mainly for industry (BEC 121); Processed industrial supplies nec (BEC 22); Processed fuels and lubrificants (BEC 32); Capital goods, except transport equipment (BEC 41); Parts and accessories (BEC 42); Industrial transport equipment (BEC 521); Parts and accessories of transport equipment (BEC 53). This definition of intermediate inputs is similar to the one employed by Goldberg et al. (2009). As a robustness check, in Section (3), we exclude capital goods, fuel and lubrificants. The results are not sensitive to changes in the definition of intermediate inputs.

Following the literature, in our analysis we mostly focus on product-partner combinations (varieties). We define a product (p)-partner (n) combination as a new variety (v), when the country imports the product from the trading partner for the first time. Similarly to the PC classification, the CN classification also undergoes several changes over our sample period. We keep track of all these changes using the year-to-year correspondence tables provided by Eurostat. We then identify variety v, imported by country c in year t, as new if either: (1) the product code p is introduced in the classification in year t and does not have any old corresponding code; or (2) the product code p is introduced in the classification in year t and has one or more old corresponding codes, but none of the latter was ever imported by country c from partner n before (i.e., since the first available year in our data); or (3) the product code p is not new to the classification, but was never imported before by country c from partner n. We use a mirror-like strategy to identify exiting varieties. Similarly to domestic products, imported varieties can be counted as new, or exiting, only once. Hence, this identification procedure is not affected by changes in the CN classification and by discontinuities in bilateral trade flows over time.

2.2 Stylized Facts

Table 1 reports information on entry and exit of domestic products, imported products, and imported varieties; all figures are in percentage and are averaged across countries and years. Panel a) shows that the entry of domestic products is not negligible: each year, in fact, new products account for 5% of all domestic goods. At the same time, the exit rate is 4.8%, which implies a substantial product churning in our sample. Turning to imports, panel b) shows that new products only account for 1.2% of all imported goods.[13] Panel c) shows, instead, that entry is much higher for imported varieties, and panel d) confirms this result for the subsample of intermediate inputs. Note, in fact, that new varieties account for 13% of all imported varieties in both samples. Churning is high also in this case, as the exit rate of imported varieties is around 10.5%.

Next, we decompose the yearly change in the value of domestic production into the contributions of three sets of products: new (New), exiting ($Exit$) and continuing ($Cont$). Similarly, we decompose the yearly change in import value into the contributions of new, exiting and continuing

[13] New imported products are 8-digit products imported for the first time from any trading partner. Similarly, exiting products are 8-digit products that stop being imported from all trading partners. Also in this case, the identification accounts for changes in the CN classification and for discontinuities in trade flows over time.

products or varieties. In all cases, we use the following formula:

$$X_{c,t} - X_{c,t-1} = \sum_{z \epsilon New_{c,t}} X_{z,c,t} - \sum_{z \epsilon Exit_{c,t}} X_{z,c,t-1} + \sum_{z \epsilon Cont_{c,t}} (X_{z,c,t} - X_{z,c,t-1}) \quad (1)$$

where t indexes years, c indexes countries, z indexes products or varieties, and X is either production or import value. As suggested by Bernard, Redding and Schott (2010), decompositions such as the one in equation (1) have two main advantages. First, being based on nominal values, they do not require product-level deflators, which are generally unavailable. Second, they can be easily converted into percentage decompositions, by dividing throughout by $X_{c,t-1}$.

In Table 2, we present the results of these decompositions. All figures are in percentage and are averaged across countries and years. Panel a) reports the decomposition for domestic production, whose average growth rate is 9.4% per year. New goods account for 24.8% of this figure.[14] As for imports, their value has increased by an average 11.7% per year. New imported products only account for 1.3% of this figure (see panel b)). The contribution of new varieties is instead much larger and equal to 17% of total import growth (see panel c)). This is consistent with our previous evidence on entry rates and with previous findings by Broda et al. (2006).[15] The picture is very similar for the subsample of intermediate inputs, as new varieties account for 20% of intermediate import growth (see panel d)). Hence, most of the action in our data comes from the addition of trading partners for existing products, rather than from the imports of entirely new products. In the following econometric analysis, we therefore focus on new imported varieties.

We organize the presentation of the econometric results in three separate sections. First, we study how new imported inputs affect the introduction of new domestic goods (Section 3). Second, we investigate the channels through which this effect occurs, by emphasizing three possible drivers: number, price and quality of new imported inputs (Section 4). Third, we unveil differences between new and existing products in terms of volumes, price and quality, and study how such differences depend on the use of new imported inputs in production (Section 5).

[14] This value is close to those reported by Goldberg et al. (2010b) and Bernard, Redding and Schott (2010), based on Indian and US firm-level data, respectively.

[15] New imported products (as opposed to new imported varieties) can be more important for the developing countries, especially in their first phase of trade liberalization. See Goldberg et al. (2009) for evidence on India.

3 Imports of New Intermediates and Introduction of New Goods

In this section, we show that new imported inputs boost product innovation. After presenting the baseline estimates, we assess their robustness and illustrate some extensions. Then, we discuss potential issues with endogeneity and identification. Finally, we perform a simple exercise to assess the economic magnitude of the effect.

3.1 Baseline Estimates

We estimate the following specification on the pooled sample of countries (c), industries (i) and years (t):

$$NP_{c,i,t} = \alpha_{c,i} + \alpha_t + \beta_1 NII_{c,i,t-1} + \varepsilon_{c,i,t}, \tag{2}$$

where $\alpha_{c,i}$ are country-industry effects, α_t are year effects and ε is a random disturbance. NP is the share of new domestic products in total domestic products; NII is the share of new over total imported input varieties (henceforth, we drop the word "varieties" for brevity). These two variables are constructed for each country, industry and year, starting from the product-level data illustrated before.

The results are in Table 3. Columns (1)-(3) estimate equation (2) by OLS, at three different levels of industry aggregation: 4-digit NACE in column (1), 3-digit NACE in column (2) and 2-digit NACE in column (3). The estimated coefficients are all positive and highly significant, with t-statistics close to 10. An increase in the share of new imported inputs is therefore associated to an increase in the share of new domestic products in the following period. Interestingly, the point estimates roughly double each time the level of industry aggregation is increased. According to column (1), in fact, a 1 percentage-point (p.p.) increase in the share of new imported inputs is associated to a 0.12 p.p. increase in the share of new domestic products; this figure rises to 0.25 p.p. in column (2) and to 0.4 p.p. in column (3). This pattern is consistent with the fact that industries source inputs not just from themselves, but also from other industries in the same aggregate group.

In order to fully accommodate backward linkages across industries, we now exploit the Input-Output Accounts provided by Eurostat (at the 2-digit industry level) for the countries in our sample. Using the Import Matrices (an element of those Accounts), we compute the share of foreign inputs purchased by any industry i from any industry k. We calculate these figures for all available years and then take their average over time.[16] Using the resulting values, $\omega_{c,i,k}$, we redefine the main explanatory variable as follows:

$$NIIov_{c,i,t} = \sum_{k=1}^{I} \omega_{c,i,k} \cdot NII_{c,k,t}. \tag{3}$$

We use the first lag of this *overall* indicator in the regressions.

Column (4) reports the results obtained by estimating equation (2) with $NIIov$ in place of NII. The coefficient β_1 is positive and highly significant also in this case, and the point estimate further increases compared to columns (1)-(3). The new coefficient implies that a 1 p.p. increase in the share of new imported inputs is associated to a 0.57 p.p. increase in the share of new domestic goods. This further confirms that backward linkages across industries are relevant for our analysis, and that the estimates of β_1 may be downward biased if such linkages are not accounted for.[17] We thus view column (4) as our preferred specification.

3.2 Robustness and Extensions

We check the robustness of the baseline results with respect to: outliers; changes in the definition of the regressor; potential issues with the dependent variable; use of values to construct the main variables; inclusion of controls for concomitant factors in the specification. We also study how the results are affected when we use alternative lags of the explanatory variable, focus on different groups of EU countries, and distinguish imported inputs by country of origin.

Accounting for Outliers We start by showing that our results are unlikely to be driven by just a few influential observations. To this purpose, in Table 4, we use a number of complementary approaches. In column (1), we trim the distributions of NP and $NIIov$ at the top and bottom 1%. In column (2) we winsorize both distributions, by replacing the observations in the bottom (top) 1% tail with the value of the 1st (99th) percentile (Angrist and Krueger, 1999). In columns (3)

[16] See Table A2 for the availability of Input-Output Accounts across countries and years.

[17] We have also estimated equation (2) by including, jointly, the share of new imported inputs within an industry (NII) and the share of new imported inputs from all other industries. Both variables enter with positive and significant coefficients, and the coefficient of the latter indicator is larger than that of the former. These results are available upon request.

and (4) we exclude, respectively, industries and countries with extreme values of NP or $NIIov$.[18] Finally, in column (5) we use an outlier-robust estimation procedure.[19] In all cases, the results are virtually unchanged.

Using Alternative Definitions of the Regressor Next, we show results obtained with alternative definitions of the explanatory variable, $NIIov$. These are reported in Table 5. Each panel corresponds to a different regression and all specifications control for country-industry and year effects. To begin with, we employ Use Matrices, instead of Import Matrices, to construct the weights in equation (3). The main advantage of the Use Matrices is that they are available for many years; the main disadvantage is that they capture cross-industry linkages in terms of domestic, as opposed to foreign, purchases of intermediates. In panel a), we average the weights over all available years; in panel b), instead, we use yearly-specific weights to fully exploit the large coverage of the Use Matrices. Reassuringly, the results are strikingly similar to the baseline estimates. Next, we reconstruct $NIIov$ using narrower concepts of intermediates. In particular, we first exclude capital goods from the definition of intermediate inputs (see footnote 12); then, we also exclude fuel and lubrificants. The results, reported in panels c) and d), are virtually unchanged.

Addressing Concerns with the Dependent Variable We now tackle two possible concerns with our dependent variable, NP. The first is related to the fact that the PC classification may adjust with some delay to the invention of new products. Indeed, until such products are assigned their own code, firms will report their production using existing codes (Pierce and Schott, 2011). In such cases, we would count these products as new with a delay. To account for this issue, we reestimate equation (2) employing a different version of NP, which is constructed using only those codes that are present in the PC classification for the entire sample period.[20] The results are in Table 6, panel a). The coefficient of $NIIov$ is slightly smaller than before, which is consistent with the fact that this specification focuses on the subsample of more "traditional" goods. Nevertheless, the point estimate remains positive and highly significant, suggesting that our results are not driven

[18] In column (3), we exclude industries with the highest or lowest average value of either variable. These are: Manufacture of tobacco products (NACE 16); Tanning and dressing of leather, manufacture of luggage, handbags, saddlery, harness and footwear (NACE 19); Manufacture of coke, refined petroleum products and nuclear fuel (NACE 23). Using the same approach, in column (4) we exclude Germany, UK, Latvia and Lithuania.

[19] Implemented using the `rreg` routine in Stata.

[20] The number of such codes is 3,098.

by this classification issue.

The second concern is related to our strategy for identifying new products. Recall that a product is defined as new, in country c and year t, if it has not been produced in that country since the beginning of the sample until t. Moreover recall that, if production resumes in t after having stopped for a while, that is not counted as entry. Such a strategy may overestimate the number of new products in the initial periods. For instance, if we observe positive production for a good in 1996, but not in 1995, we consider that as entry, even though we do not know whether the good was produced before (say in 1994 or earlier). The strategy becomes more conservative, and thus reliable, as time passes and we can track production back for a longer period.[21] Hence, in panels b)-d), we reestimate the baseline specification after excluding, respectively, the first year, the first two years, and the first three years of observations for each country. As expected, the coefficient of $NIIov$ slightly decreases, but remains positive and highly significant.[22]

Constructing Variables Using Values So far, we have used numbers of products (domestic goods or foreign inputs) to construct the variables in equation (2). This approach implicitly assumes that all products have equal weight, independently of their value. We now reconstruct NP and $NIIov$ using values instead of numbers. In particular, we redefine NP as the share of new goods in the total value of domestic production, and $NIIov$ as the share of new imported inputs in the total value of imported intermediates. In this way, we give higher weight to products with larger values. The results are in Table 7. In column (1) we redefine only $NIIov$, in column (2) only NP, and in column (3) both variables at the same time. Note that the coefficients are generally larger than before, suggesting that goods/inputs with small values contribute less to the relationship than those with large values. The baseline estimates therefore capture the lower bound of the effect of new imported inputs.[23]

[21] For this reason, the issue is less relevant for the trade data, which usually start well before the estimation sample (see Table A2).

[22] We have also experimented by excluding the first four and five years of observations. The results did not change. Note, however, that three years of observations is the maximum we can exclude without having to drop any country from the estimation sample.

[23] Columns (2) and (3) use fewer observations than column (1), because some production values are not reported in PC for confidentiality reasons. When this happens, we know that production has occurred, but we do not observe its value. We can thus use these observations when working with numbers, but not when working with values. Note that the higher point estimates in columns (2) and (3) are unlikely to be driven by the change in sample size. In fact the coefficient of $NIIov$, obtained by estimating equation (2) on that subsample using variables in numbers, is equal to 0.598 (s.e. 0.085), i.e., it is very similar to our baseline estimate.

Adding Controls for Industry and Country Characteristics Next, we extend the baseline specification by adding controls for industry and country characteristics. These controls should account for factors correlated with new imported inputs and the introduction of new products. The results are in Table 8. As for industry-level controls, we start by including capital and material intensity ($KINT$ and $MINT$), labor productivity ($LPROD$) and employment ($EMPL$). None of these variables has a statistically significant coefficient, and the main results are largely unchanged (see column (1)). Then, we also add overall import penetration ($IMPINT$, defined as imports over the sum of imports plus output) and a proxy for technical change ($TECH$, defined as the high-tech share of capital investment).[24] The coefficients of these variables are only marginally significant, and the main evidence on new imported inputs is qualitatively unaffected (see column (2)).[25] Finally, we replace the time dummies with a full set of interactions between industry and time effects, which account for industry-specific shocks in a flexible and comprehensive way. The main results do not change (see column (3)).

As for country-level controls, we first include standard variables such as the level and growth of per capita GDP (GDP and $GDPGR$), population size (POP), the real exchange rate ($EXCH$), and the ratios of merchandise trade and gross fixed capital formation to GDP ($TGDP$ and $KGDP$).[26] The coefficients of these controls are highly significant and generally have the expected sign, but the evidence on new imported inputs is largely unchanged (see column (4)). Finally, we replace the year dummies with country-time effects, so as to further account for country-specific shocks. The main evidence is qualitatively preserved (see column (5)).

Controlling for Entry and Exit of Inputs and Products We now extend the baseline specification to discuss the role of new domestic inputs, total imported inputs, exiting inputs and products, and new imports of final goods. The results are in Table 9. In column (1), we add the share of new over total domestic inputs (NDI), constructed as in equation (3) using weights from the Use Matrices. The coefficient of this variable is positive and highly significant, suggesting that new domestic inputs stimulate as well product innovation. However, the coefficient of NDI is an order

[24] Another proxy for technical change, R&D intensity, is not available for all countries and industries in our sample.

[25] Note that all the industry-level controls used in Table 8 also vary across countries. They are sourced from the EUKLEMS database (O'Mahony and Timmer, 2009), with the exception of import penetration (constructed using Comext data).

[26] These variables are sourced from the World Development Indicators.

of magnitude smaller than that of $NIIov$.[27] Hence, while all new inputs matter, foreign ones have a much larger impact on domestic product innovation.

Columns (2) and (3) add the shares of imported inputs in total import value (IIV) and total number of imported varieties (IIN), respectively. Both variables have small and poorly identified coefficients, and their inclusion leaves the estimate of interest virtually unchanged. Hence, our results do not merely reflect the overall expansion of trade in intermediates over the sample period (see Feenstra, 1998 and Yi, 2003 on this point); rather, they highlight a crucial role for *new* imported inputs.

Column (4) adds the shares of exiting inputs in the total number of domestic and imported intermediates ($EXDI$ and $EXII$, respectively), whereas column (5) adds the share of exiting products in the total number of products (EXP). All these indicators have small and imprecisely estimated coefficients, and the main results remain unchanged. While some countries and industries have undergone deep structural changes over the sample period - with simultaneous adding and shedding of inputs and products - our findings are unlikely to be driven by these transformations, and thus imply an autonomous role for new imported inputs.[28]

Finally, column (6) adds the share of new over total imported varieties of *final* goods (NFG), computed as in equation (3). Its coefficient is small and not significant, while that of $NIIov$ remains largely unchanged. This suggests that the type of new imported goods is crucial for product innovation: while new imported inputs stimulate product innovation, new final products do not play any role.

Using Alternative Lags In Table 10, we revisit the effect of new imported inputs at different lag lengths. In particular, we study the contemporaneous effect using the current period value of $NIIov$, and the delayed effect using up to five lags of this variable. Each panel of the table corresponds to a different regression and all specifications control for country-industry and year effects. Interestingly, the estimated coefficient is positive, significant, and largely stable in size up to the third lag, whereas it drops and becomes insignificant afterwards. This pattern is broadly consistent with existing models of endogenous growth, according to which the effect of new imported

[27] It is worth noting that the sample means of NDI and $NIIov$ equal 7% and 13%, respectively.

[28] Instead of controlling for exit of domestic products as in column (5), we have also estimated equation (2) using net entry as the dependent variable. (Net entry is defined as the share of new, minus exiting, products in total domestic products.) We have found very similar results, as the coefficient of $NIIov$ was equal to 0.411 (s.e. 0.083).

inputs may weaken over time (see, e.g., Rivera-Batiz and Romer, 1991).

Exploring Heterogeneity Finally, we explore potential dimensions of heterogeneity in the previous findings. The results are in Table 11. First, we study how the effect of new imported inputs differs across EU countries. To this purpose, in column (1) we add to the baseline specification an interaction term between $NIIov$ and a dummy for the ten New Members.[29] Both the linear term and the interaction are positive and highly significant, and the latter coefficient is almost twice as large as the former. Hence, new imported inputs stimulate product innovation in both groups of EU countries, but their effect is stronger for the New Members than for the more mature economies of the EU15.

Next, we investigate how the results differ depending on a country's degree of product market regulation (PMR), as introducing new products may in principle be easier where PMR is weaker. For each EU country, we measure PMR using the OECD index, averaged across all available years. We then identify countries with weak PMR as those where the index is below the median, and countries with strong PMR as all the others. In column (2), we interact $NIIov$ with a dummy equal to 1 for countries with weak PMR. As expected, the interaction term is positive, albeit imprecisely estimated.

Finally, we distinguish new imported inputs by country of origin. In particular, we split up the explanatory variable in two separate regressors, one for imports from OECD countries and the other for imports from non-OECD countries. As shown in column (3), both variables have positive and significant coefficients, and the point estimate is larger for OECD imports.

3.3 Identification

A concern with our baseline results is the possible endogeneity of new imported inputs in equation (2), which may be due to simultaneity and reverse causality. Simultaneity occurs if NP and $NIIov$ are jointly determined, due to unobserved shocks at the country and industry level. Reverse causality instead occurs if firms first innovate and then start importing the necessary inputs. In the previous section, we have shown that our results are robust, among other things, to the use of longer lags of $NIIov$ and to the inclusion of controls for observed, and unobserved, concomitant factors. In this

[29] Eastern European countries that joined the EU in 2004 or 2007.

section, we tackle the endogeneity concern directly, by using two complementary approaches. First, we estimate our baseline specification by Instrumental Variables (IV), using plausibly exogenous instruments for $NIIov$. Second, we exploit a series of trade shocks to identify the effect of new imported inputs.

IV Regressions We need our instruments to pick up the fraction of variation in the share of new imported inputs which is exogenous to product innovation decisions within individual industries in each country. Our preferred set of instruments captures two possible determinants of such an exogenous variation. The first determinant is any technological shock allowing trading partners to produce and export new intermediate inputs.[30] If such a shock occurs, imports of intermediates will increase not just in the EU, but also elsewhere in the world. Hence, as our first instrument, we use imports of intermediates in the US. Exploiting highly detailed product-level data from Feenstra et al. (2002), we compute US intermediate imports from all trading partners in the world, excluding each time the EU country to which the instrument refers. We aggregate these data at the 2-digit industry level, and so obtain a variable that varies across countries, industries and years.[31] The second determinant we consider is any reduction in trade barriers that makes it profitable for foreign firms to start exporting inputs.[32] Hence, as our second instrument, we use average US tariffs on imported inputs. Changes in US tariffs are likely to be correlated with changes in EU tariffs; however, given that we focus on product innovation in the EU, they are less likely to be plagued by endogeneity concerns arising from the usual political economy argument. As done for the import data, for each 2-digit industry we calculate average input tariffs across all trading partners, except the EU country to which the instrument refers. We weight both variables by Import Matrix coefficients as in equation (3) and, to further alleviate endogeneity concerns, we use their sixth lag in all the regressions.[33]

The first four columns of Table 12 report the Two-Stage Least Squares (2SLS) results; standard

[30] Debaere and Mostashari (2010) suggest that technological progress is indeed one of the leading forces inducing countries to export new goods.

[31] US trade data are classified according to the Harmonized System (HS) classification. They are available for all 10-digit product codes and all trading partners in the world. We first identify intermediate inputs, by mapping the HS classification into the BEC classification. Then, we aggregate intermediate imports at the 5-digit level of the SITC classification. Finally, we convert these data at the 2-digit level of the ISIC classification, which is equivalent to NACE.

[32] See Kehoe and Ruhl (2009) and Debaere and Mostashari (2010) for a discussion of how lower tariffs contribute to increasing trade in new goods.

[33] Note that trade and tariffs data are available since 1989, whereas our estimation sample starts in 1995.

errors are corrected for clustering within country-industry pairs. In column (1) we use both instruments jointly. The Cragg-Donald F-statistic comfortably passes the threshold of 10 for instruments' relevance (Staiger and Stock, 1997). At the same time, the Hansen test does not reject the validity of the overidentifying restriction. Importantly, the coefficient of $NIIov$ is positive and highly significant. In the next two columns, we rerun the 2SLS regression using each instrument separately - US input tariffs in column (2) and US imported inputs in column (3) -, so as to check that the previous results are not driven by poor performance of any instrument. Since now the models are exactly identified, the Hansen statistic cannot be computed. Reassuringly, the results hold unaffected in both cases. If anything, these instrumental variables regressions reinforce the main message of the previous sections: new imported inputs stimulate domestic product innovation.

Next, we use a different instrument for robustness: the shift-share instrument used by Card (2001) and recently applied to imported inputs by Ottaviano et al. (2010). This is constructed as follows. For each country c, industry i and period t, we compute the share of new imported inputs from partner n in the total number of imported inputs: i.e., $NII_{c,i,n,t}$, such that $\sum_n NII_{c,i,n,t} = NII_{c,i,t}$. We regress this variable on full sets of industry-period and partner-period effects, separately for each EU country in the sample. Then, we apply the partner-period effects to the initial value of $NII_{c,i,n}$, i.e., the value observed in the first year for which trade data are available (usually, well before the beginning of the estimation sample, see Table A2). Finally, we aggregate the resulting variable across all trading partners, separately within each country, industry and year. This instrument isolates the variation in the share of new imported inputs due to partner-specific shocks. To illustrate, consider two industries in country c and suppose that, in the initial period, they have the same total share of new imported inputs. Also assume, however, that partner n accounts for a larger fraction of new imported inputs in one industry than in the other. If partner n experiences a shock that raises its overall exports of new intermediates to country c, the instrument will impute a larger exogenous increase in the supply of new foreign inputs to the former industry than to the latter. The 2SLS results using the shift-share instrument are reported in column (4). Note that they are very similar to those obtained with our preferred instruments set.

Next, we reestimate the baseline specification by pooled-IV Tobit, so as to account also for left-censoring in the dependent variable.[34] We use our preferred instruments and correct the standard

[34] The number of zero observations is 1,454, about one-third of the sample.

errors for clustering within country-industry pairs. The results, reported in column (5), are similar to those obtained by 2SLS. Finally, we use the two-step system-GMM estimator developed by Blundell and Bond (1998).[35] As before, we treat $NIIov$ as endogenous and instrument it with our preferred instruments. The results are in column (6). Both the Hansen and the Sargan test cannot reject the validity of the overidentifying restrictions. At the same time, the AR 2-test suggests no 2nd-order serial correlation in the residuals. Note that the lagged dependent variable has a positive and significant coefficient, implying that product innovation is persistent (see Parisi, Schiantarelli and Sembenelli, 2006, on this point). More importantly, the coefficient of $NIIov$ remains positive and very precisely estimated.

Trade Shocks Our second strategy to tackle endogeneity is to exploit a series of trade shocks occurred over the sample period. We work under the following identifying assumption. These shocks have caused a reduction in the cost of trading inputs, which was independent of product innovation decisions within individual country-industry pairs. As a result, the set of foreign inputs available for production has exogenously expanded, and this has boosted product innovation.[36] We consider three types of shocks: to trading partners, to individual inputs and to EU countries.

The first shock we consider is the WTO membership obtained by a total of 35 trading partners since 1996. We restrict attention to these countries and recompute the variable $NIIov$ using only inputs sourced from them. We then use this new regressor to reestimate our baseline specification by 2SLS. As instruments, we use the sixth lags of US imported inputs and input tariffs from these 35 countries. The results are in Table 13, column (1). Note that the estimated coefficient is positive, very precisely estimated, and close in size to that in Table 12 (column (1)). In column (2), we repeat the exercise focusing only on China, the largest of the New WTO Members. Strikingly, the results are very similar and possibly slightly stronger.

Next, we consider a shock to individual inputs. We note that, over the sample period, tariff reductions were not uniform across product lines, as some intermediates have experienced larger tariff cuts than others. We thus reestimate our baseline specification using only inputs with large tariff cuts, for which trade costs have declined more abruptly. We identify these inputs using data

[35] We transform variables in forward orthogonal deviations, collapse the GMM instruments, and use Windmeijer's (2005) finite-sample correction for the standard errors.

[36] Goldberg et al. (2010a) provide an interesting example of how an exogenous trade shock (trade liberalization in India) can enlarge the set of imported inputs used by firms and, through this channel, expand their product scope.

on US input tariffs. In particular, for each input we compute the average tariff change between 1989 and 2006, and then keep only inputs with tariff cuts above the median.[37] We then identify the same intermediates in our European data, and use them to recompute $NIIov$. As an instrument for this new regressor, we use the sixth lag of US imported inputs, again restricting to inputs with large tariff cuts. The results are in column (3). Reassuringly, the estimated coefficient remains positive, highly significant and stable in size.[38]

Finally, we consider shocks to our sample countries. Two such shocks have occurred since 1995: (1) adoption of a common currency, which involved twelve EU countries in 1999 (2000 for Greece); (2) accession to the EU, which involved ten other countries either in 2004 or in 2007. We exploit these shocks as follows. We split the sample in two (mutually exclusive) groups of countries, the first composed of the twelve economies that adopted the Euro, and the second consisting of the ten New Members. We then estimate the following specification by OLS, separately on each subsample:

$$NP_{c,i,t} = \alpha_{c,i} + \alpha_t + (\beta_1 + \beta_2 \mathbf{I}\{t \geq s_c\}) \cdot NIIov_{c,i,t-1} + \varepsilon_{c,i,t}, \tag{4}$$

where $\mathbf{I}\{\cdot\}$ is the indicator function, which takes the value 1 in country c when the shock occurs (year s_c) and in all subsequent periods. Note that equation (4) is a difference-in-differences specification with a continuous treatment (Wooldridge, 2002). We expect the effect of new imported inputs to be stronger after the trade shock, i.e., $\beta_2 > 0$. The results are in column (4) for the Euro Area countries and in column (5) for the New EU Members. Note that, in both cases, β_2 is positive, large and very precisely estimated.

3.4 Economic Magnitude

In this section, we assess the economic significance of the effect of new imported inputs, by means of a simple back-of-the-envelope calculation. First, we estimate the relationship between new imported

[37] We work with 6-digit HS products, as the HS and CN classifications coincide at that level of aggregation. The number of inputs with tariff cuts above the median is 1,348. For these inputs, the average yearly tariff cut ranges from a minimum of 0.2 p.p. to a maximum of 21.5 p.p..

[38] Since we use US input tariffs to identify the intermediates employed in column (3), our second instrument is endogenous and we must discard it. Indeed, if we also used that instrument, the Hansen test would reject the validity of the overidentifying restriction at the 10% level. The estimated coefficient would be equal to 1.020 (s.e. 0.111).

inputs and the percentage contribution of new products to output growth (CNP):

$$CNP_{c,i,t} = \alpha_{c,i} + \alpha_t + \underset{(0.114)}{0.509^{***}} \cdot NIIov_{c,i,t-1} + \varepsilon_{c,i,t}. \tag{5}$$

Next, we note that in our sample the average entry rate of new imported inputs is 13% per year (see Table 1). Multiplying this number by the estimated coefficient in equation (5), we obtain that new imported inputs account for roughly one-fourth of the contribution of new products to output growth observed in our sample (24.8%, see Table 2).

4 Channels

The previous section has shown that new imported inputs stimulate product innovation. Our aim in this section is to discuss the channels through which this effect occurs. Following the relevant empirical work in this area (in particular, Goldberg et al., 2010a and Kugler and Verhoogen, 2009), we analyze the three following mechanisms: (1) expansion in the number of available intermediates, which allows producing new goods in the presence of essential inputs; (2) access to cheaper inputs, which makes it profitable to produce goods otherwise too costly; (3) access to higher quality inputs, which renders the manufacturing of some products technologically feasible.

We analyze the three channels jointly by estimating variants of the following specification:

$$\begin{aligned} NP_{c,i,t} &= \alpha_{c,i} + \alpha_t + (\beta_1 + \beta_2 PNew_{c,i,t-1} + \beta_3 QNew_{c,i,t-1}) \cdot NIIov_{c,i,t-1} + \\ &\quad + \beta_4 PNew_{c,i,t-1} + \beta_5 QNew_{c,i,t-1} + \varepsilon_{c,i,t}, \end{aligned} \tag{6}$$

where $PNew$ and $QNew$ are the average price and average quality of new imported inputs, relative to existing imported inputs (see below). The effect of new imported inputs on the introduction of new products is then given by:

$$\frac{\partial NP}{\partial NIIov} = \beta_1 + \beta_2 PNew + \beta_3 QNew \tag{7}$$

and varies across observations. If $\beta_2 = \beta_3 = 0$, the right-hand side of equation (7) boils down to β_1. The effect of new imported inputs is thus independent of their price and quality. In this case, new imported inputs stimulate product innovation only by expanding the number of available intermediates (the first channel). Otherwise, new imported inputs also work through price and quality differences relative to existing inputs (the second and third channels, captured by β_2 and β_3, respectively).

To construct $PNew$, we normalize the price (unit value) of each imported input variety so as to range between zero and one;[39] then, we divide it by the average price of all imported inputs in each country, 4-digit industry and year. In this way, we make prices comparable across countries and industries, by removing systematic differences in the type of imported inputs. Next, we average this ratio over new imported inputs, thereby obtaining a proxy for their relative price in each country, 4-digit industry and period. Finally, we compute the weighted average of these relative prices at the 2-digit level; as weights, we use the share of each 4-digit industry in the total number of new imported inputs in the corresponding 2-digit industry. The resulting variable can be zero or positive; a larger number indicates a higher relative price of new imported inputs. For estimation, we weight this variable using Import Matrix coefficients, as in equation (3).

We use the same approach to construct the variable $QNew$. Unlike prices, however, quality is not observed in the data, so we first need to estimate it. We accomplish this task by using the methodology developed by Khandelwal (2010). This simple and tractable approach yields time-varying estimates of quality at the level of individual imported varieties. In brief, the quality estimates are obtained by adding up the variety fixed effect, the time fixed effect and the residual, from a regression of each variety's market share (in an industry) on its price and other controls: higher quality therefore means higher market share conditional on prices. As detailed in the Appendix, we apply Khandelwal's methodology separately on each 4-digit industry in each country.[40] As a result, we build up a novel and complete data set of quality estimates for all imported varieties in all EU countries. We use these estimates to construct the variable $QNew$, in exactly the same way as we used prices to construct $PNew$.

The results are in Table 14. For the sake of comparability, we first reestimate our baseline specification (see equation (2)) on the subsample with non-missing values of $PNew$ and $QNew$.

[39] We perform this normalization within countries, 4-digit industries and years.

[40] This implies that the quality estimates are not comparable across countries and industries. We thus normalize them by country-industry-year means, as we did for prices (see above). Later on, in some robustness checks, we will regress the quality estimates (and the prices) on product fixed effects, so as to further alleviate this concern.

The coefficient β_1, reported in column (1), is similar to our baseline estimate. In column (2), we add $PNew$ and its interaction with $NIIov$. The coefficient β_1 halves, suggesting that part of the effect of new imported inputs does not come through the first channel. Note, in fact, that the coefficient β_2 is positive and statistically significant, implying that the effect of new imported inputs grows stronger with their relative price.

If higher prices are a signal of higher quality, the previous result suggests that new imported inputs have a stronger effect on product innovation the higher is their relative quality.[41] Unlike previous studies, we have separate information on prices and quality, so we can investigate this issue in depth. We can also explore whether price differences matter even *conditional* on quality differences.

To begin with, we note that $PNew$ and $QNew$ are positively correlated in our sample: controlling for country-industry and year effects, the correlation is 0.82, with a standard error of 0.029. This is consistent with the insight from Kugler and Verhoogen (2009), that higher input prices signal higher input quality. Next, we estimate the complete version of equation (6), by further adding $QNew$ and its interaction with $NIIov$. Given that $QNew$ is based on quality estimates obtained in a first stage, we report bootstrapped standard errors (based on 100 replications) followed by analytical standard errors corrected for clustering within country-industry pairs.

The results are in column (3). We highligth three important findings. First, the coefficient β_3 is positive and highly significant, confirming that the effect of new imported inputs grows stronger as their quality increases. This suggests that the third channel mentioned at the beginning is empirically relevant in our case. Second, the coefficient β_2 turns negative and is very precisely estimated. After controlling for relative quality, the effect of new imported inputs is stronger the *lower* is their relative price. We view this result as consistent with the second channel recalled above. Finally, the coefficient β_1 drops to zero and becomes insignificant, suggesting that the first mechanism is not quantitatively relevant in our sample.

Next, we assess the robustness of these results with respect to alternative ways of estimating quality. As detailed in the Appendix, we perform two crucial checks suggested by Khandelwal

[41] See Kugler and Verhoogen (2009) for an extensive discussion of the positive association between input prices and input quality. More generally, see Schott (2004), Hummels and Skiba (2004), Hallak (2006), Choi et al. (2009), Manova and Zhang (2010) and Hallak and Schott (2011) for leading contributions using unit values in trade-flow data to infer quality.

(2010): in column (4), we exclude the residual from the definition of quality while, in column (5), we use quality estimates obtained by OLS rather than 2SLS. We also perform two additional checks that we believe to be relevant in our context. First, we repeat the quality estimation procedure on the whole sample of imported varieties, rather than on the subsample of imported inputs (column (6)). Second, we regress quality and prices on product fixed effects, so as to further clean up these variables from product and industry characteristics; we then use the residuals from these regressions to reconstruct $QNew$ and $PNew$ (column (7)). As is clear from the table, our main results are robust across all these sensitivity checks.

Finally, we discuss the economic magnitude of the effect of new imported inputs. First, we compute the average value of $PNew$ and $QNew$ for each country-industry pair. Then, we evaluate the derivative in equation (7) at each observation of the resulting sample. We compute the standard errors of the derivative using the bootstrapped standard errors of the parameters. The bottom part of the table contains the results. To save space, we report the mean and a few relevant percentiles of the distribution of the effect. The average effect is positive and highly significant across all specifications. The point estimate implies that a 1 p.p. increase in the share of new imported inputs raises the share of new products by about 0.65 p.p., which is in line with the results in column (1) and in the previous section. More interestingly, while the effect could be negative in country-industry combinations where new imported inputs have high relative prices and low relative quality, we find positive and highly significant results across the entire distribution. In particular, the effect ranges from about 0.45 at the 10th percentile to about 0.85 at the 90th percentile.

5 Characteristics of New Products

We now study how new products compare with the existing ones in terms of volumes and prices, and how the differences depend on the use of new imported inputs in production. With these aims in mind, we estimate the following specifications using product-level data:

$$\ln x_{c,i,p,t} = \alpha_p + \alpha_{c,t} + \beta_1 New_{c,i,p,t} + \varepsilon_{c,i,p,t} \tag{8}$$

and

$$\ln x_{c,i,p,t} = \alpha_p + \alpha_{c,t} + (\beta_1 + \beta_2 NIIov_{c,i,t-1}) \cdot New_{c,i,p,t} + \\ + \beta_3 NIIov_{c,i,t-1} + \varepsilon_{c,i,p,t}, \tag{9}$$

where x is either volume or price, α_p are product fixed effects, $\alpha_{c,t}$ are country-year fixed effects and New is a dummy for new products. The product fixed effects absorb all systematic differences in product and industry characteristics. The country-year effects allow us to compare new and existing goods within the same country in the same year. As standard in the empirical literature, we exclude extreme observations with unit values in the top and bottom decile of the distribution.

The estimates of equation (8) are in Table 15, using volumes in columns (1)-(2) and prices in columns (5)-(6). Not surprisingly, column (1) shows that new products sell in lower volumes than existing products. The point estimate implies, in fact, that the quantity sold of new goods is about half that of existing goods.[42] The evidence is largely unchanged in column (2), where we exclude goods whose production stops in the following period (exiting products).

Turning to prices, column (5) shows that new products exhibit a substantial premium over existing products. According to the point estimate, in fact, the average price of new goods is 4% higher than that of existing goods. When exiting products are excluded from the sample, the point estimate hardly changes (see column (6)). Overall, these results show that new goods are sold in lower volumes relative to existing goods, and that consumers pay higher prices for them.

We now ask whether, and to what extent, these differences are influenced by new imported inputs within industries. Columns (3) and (4) report the estimates of β_1 and β_2 from the volume specification of equation (9), whereas columns (7) and (8) report those from the price specification. Starting from the volume specification, the estimate of β_2 is negative, though not significant, both on the whole sample of products (column (3)) and on the subsample excluding exiting goods (column (4)). At the same time, β_1 remains negative, highly significant, and close in size to the estimates in previous columns. Hence, new products sell in lower volumes relative to existing products, and the difference is at most modestly influenced by new imported inputs.

The evidence on prices is starker. Columns (7) and (8) show that β_2 is positive and very precisely

[42] As standard for specifications like (8), the average percentage difference between new and existing products is computed as $(\exp(-0.742) - 1) * 100 = -52.4\%$.

estimated on both samples of goods, whereas β_1 drops and becomes insignificant after accounting for new imported inputs. Absent new imported inputs, therefore, new products are not priced more than existing products. However, the price difference becomes quickly positive, and grows rapidly, as new imported inputs increase. To have a sense of this, note that the price premium of new goods equals 4.5% at the mean of $NIIov$ (13%) and reaches 9.6% at the 90th percentile (20%). We conclude that, besides facilitating product innovation, new imported inputs induce industries to introduce goods with different characteristics: in particular, goods that sell at higher prices relative to existing products.

In the remaining part of this section, we ask how consumers perceive the quality of new goods relative to that of existing goods. We also ask how quality differences depend on the use of new imported inputs in production. Khandelwal's (2010) procedure does not allow estimating quality for domestic goods. To shed some evidence on these issues, we therefore use his quality estimates for US imports. In particular, we compare quality between new and existing exports from the EU to the US, and study how the difference depends on the use of new imported inputs in the EU. To carry out this exercise, we match Khandelwal's (2010) quality estimates with our data on new exported products to the US.[43]

Before commenting the results, we pause to motivate our use of export data and, in particular, of exports to the US. First, we note that new imported inputs increase the share of new exported varieties in as much the same way as they increase the share of new domestic products. In particular in a regression like (2), using the share of new exported varieties as the dependent variable, the coefficient of $NIIov$ equals 0.488 (s.e. 0.180). Second, we recall that the US is the main market for EU exports, as it accounts for the largest share (21%) of extra-EU trade.[44] Third, we document that the differences between new and existing exports, in terms of volumes and prices, strikingly resemble those unveiled for domestic products. This fact emerges from Table 16, columns (1)-(4), where we regress log export volumes and log export prices on dummies for new exported products or varieties, controlling for product and country-time effects. The estimated coefficients are negative and highly significant in the volume specifications, and positive and highly significant in the price

[43] Khandelwal estimates qualities using trade data from Feenstra et al. (2002), which are available for individual partners, years and 10-digit HS products. We use medians of the quality estimates within partners, years and 6-digit products. As already mentioned, in fact, at that level of aggregation the HS and CN classifications coincide. We limit the analysis to products with unique unit of measurement.

[44] This figure is drawn from Eurostat and refers to 2007.

specifications. Finally, we show that these differences persist, and remain of similar magnitude, also for the subset of new products exported to the US. This fact emerges from columns (5) and (6), where we regress log import volumes and log import prices in the US (retrieved from Khandelwal, 2010) on a dummy equal to 1 for new EU exports to the US, controlling for product and year effects. Within a given year, new EU exports sell in smaller volumes (-54%), but at higher prices (+3.3%), relative to existing EU exports.[45,46]

We now go back to the question of how quality differs between new and existing goods. In column (1) of Table 17, we regress Khandelwal's quality estimates on a dummy equal to 1 for new exported goods to the US, controlling for product and year effects. Because quality estimates only have an ordinal meaning, we standardize the dependent variable to have zero mean and unitary variance. Moreover, since qualities are estimated in a first stage, we report bootstrapped standard errors based on 100 replications. The results indicate that the quality of new goods is significantly higher (0.04 standard deviations) than that of existing products.

Next, we split the sample in two groups of products, characterized by long and short quality ladders, respectively. Khandelwal (2010) constructs the ladder's length as the difference between the maximum and the minimum quality across all varieties within a product, in the first year it appears in the sample.[47] Products with longer ladders feature greater scope for quality differentiation, so we expect the previous findings to be stronger in the subsample of long-ladder products.[48] The results, reported in columns (2) and (3), confirm our expectations. The estimated coefficient is in fact positive, large, and highly significant for long-ladder products, whereas it is small and imprecisely estimated for short-ladder products.

Finally, we ask how the quality premium of new goods depends on the use of new imported

[45] We have also run these last specifications using a different control group, which consists of the old EU exports to the US, plus the new and existing exports to the US from any other country. The price premium of new EU exports rises to 38% ($t = 16.1$) and the volume difference to -61% ($t = 23.3$).

[46] It has to be noted that Khandelwal's quality estimates are only available for differentiated products. To further ease comparability between the results for domestic goods and those for exported goods, we have reestimated equation (8) on the subsample of differentiated domestic products (as identified using Rauch's (1999) classification). Also in this case, we have found that new goods exhibit lower volumes (-53.4%) and higher prices (+5.2%). It is also worth mentioning, following the discussion in Amiti and Khandelwal (2010) that, by using exports to a rich market like the US, we are probably picking up the highest quality goods produced by the EU, as there is evidence that higher quality goods are exported to higher income countries (Hallak, 2006; Crinò and Epifani, 2010; Manova and Zhang, 2010). This issue would be relevant for us, if the quality difference between the domestic and the exported version of a product was systematically larger in the case of *new* exports, which is however not straightforward.

[47] Note that ladder length is highly persistent over time: the correlation between a product's ladder length at the beginning and end of the sample is 0.75 (Khandelwal, 2010).

[48] In our analysis, long-ladder products are defined as 6-digit products with ladder length above the median.

inputs in production. Column (4) reports the coefficient of the dummy for new exports to the US and that of its interaction with $NIIov$. Interestingly, the linear coefficient becomes insignificant after accounting for new imported inputs: hence, if the industry does not rely on new imported inputs, new goods do not exhibit any quality premium. The interaction term is instead positive and significant, suggesting that the quality premium of new goods becomes larger as the use of new imported inputs increases. In particular, the quality premium equals 0.035 standard deviations when evaluated at the mean of $NIIov$, and 0.07 standard deviations when evaluated at the 90th percentile. Column (5) shows that these results are even stronger in the subsample of long-ladder products. For short-ladder products, instead, the pattern of sign is preserved but the coefficients are smaller and imprecisely estimated (see column (6)).

6 Conclusion

In this paper, we have studied the effects of new imported inputs on the introduction and the characteristics of new domestic products. Focusing on 25 EU countries over 1995-2007, we have shown that new imported inputs have a positive effect on domestic product innovation. This effect is directly proportional to the quality of new imported inputs and inversely related to their price (conditional on quality). Finally we have shown that, compared to existing goods, new products are sold in smaller volumes and at higher prices, and consumers perceive them as being of higher quality. The price and quality premia are stronger the higher is the use of new imported inputs in production.

These results may have important implications for policy. In particular, they are at odds with the widespread concern that ever increasing imports may only harm manufacturing firms in industrialized countries. On the contrary, our findings suggest that favoring trade in intermediates may be an effective strategy for fostering product innovation and output growth. Moreover, by stimulating the introduction of upgraded goods (i.e., goods with higher prices and higher quality), new imported inputs may facilitate the necessary shift of manufacturing toward the production of vertically superior goods, consistent with the comparative advantage of EU countries.

In conclusion, we suggest two possible lines for future research. First, the use of rich firm-level datasets, which are becoming available at rising speed and growing coverage, may complement the present analysis, by allowing researchers to unveil differences in the effect of new imported inputs across heterogeneous firms. Second, new imported inputs may potentially generate welfare gains for a country, by allowing consumers to get access to more and higher-quality goods. A rigorous welfare analysis, which is beyond the scope of this paper, may thus constitute another promising avenue for further research.

A Quality Estimation

In order to construct the variable $QNew$ used in Section (4), we need time-varying estimates of quality for individual varieties of imported inputs. We obtain these estimates using the approach developed by Khandelwal (2010). In this section, we heavily build on his work to explain the methodology.

In period t, demand for variety v has the following expression (we omit country and industry subscripts, because the specification refers to a single 4-digit NACE industry in a single country):[49]

$$\ln(s_{v,t}) - \ln(s_{0,t}) = \lambda_v + \lambda_t + \alpha \ln \pi_{v,t} + \sigma \ln(ns_{v,t}) + \lambda_{v,t}. \tag{10}$$

$s_{0,t}$ is the market share of an outside variety (domestic product), which is set to 1 minus the industry's import penetration.[50] $s_{v,t}$ is variety v's market share in the 4-digit industry, and is defined as $q_{v,t}/MKT_t$, where $q_{v,t}$ is the quantity of v and $MKT_t \equiv \sum_{v \neq 0} q_{v,t}/(1 - s_{0,t})$. $\pi_{v,t}$ is the (c.i.f.) price of variety v. $ns_{v,t} \equiv q_{v,t}/\sum_{v \in p} q_{v,t}$ is variety v's share in the corresponding (8-digit CN) product p (i.e., the nest share). $\widetilde{\lambda}_{v,t} \equiv \lambda_v + \lambda_t + \lambda_{v,t}$ captures quality: conditional on prices, higher-quality varieties exhibit greater market shares. The term λ_v is the time-invariant valuation of v (variety fixed effect), the term λ_t is the secular time trend common across varieties (year fixed effect), and the term $\lambda_{v,t}$ is a variety-time-specific deviation (residual). Following Khandelwal (2010), we add partner n's population to equation (10), in order to control for hidden varieties.[51]

[49] This expression is derived under the nested logit framework introduced by Berry (1994). This framework prevents the quality estimates from being influenced by the fact that varieties are closer substitutes within products (the *nests*) than between products.

[50] Import penetration is defined as imports over the sum of imports plus output. We calculate import penetration separately for each country, 4-digit industry and year, using import and turnover data from Eurostat.

[51] A partner n could export different subproducts of p, classified under more finely detailed categories than those available in the trade data (hidden varieties). This would increase the market share of variety v, even if all subproducts were of the same quality as the exports of p from other partners. Population size controls for hidden varieties. We use data from the World Development Indicators.

We estimate three different versions of the model, separately on each 4-digit industry in each of the countries in our sample. The first, and preferred, version is estimated by 2SLS on the subsample of intermediate inputs. The second version is estimated by OLS on the same subsample. The third version is estimated by 2SLS on the whole sample of products (i.e., including also the imported varieties of final goods). As discussed by Khandelwal (2010), 2SLS account for possible correlation between $\pi_{v,t}$ and $ns_{v,t}$ on one side, and $\lambda_{v,t}$ on the other. Following Khandelwal's work, we use the following instruments to estimate the first and third version of the model: number of varieties within each product p, number of varieties exported by each trading partner n, and interactions between distance from n and oil prices, and between distance from n and product-specific transportation costs.[52] Finally, prior to estimation we exclude varieties with extreme unit values (i.e., below the 5th or above the 95th percentile of the distribution within industries, see Khandelwal, 2010), and drop industries with fewer than 20 varieties observed at least twice.

Table A1 reports summary statistics on the results for the three models. We perform 3,268 separate regressions when working with the subsample of intermediate inputs, and 4,205 when working with the whole sample of products. Overall, we use 10 million observations in the first case and 15 million in the second. The median number of observations per estimation is 1,651 and 1,959 respectively, whereas the median number of varieties per estimation is 460 and 552. The median price elasticity is negative, whereas the median coefficient of the nest share is positive. This pattern of sign matches that in Khandelwal (2010). More importantly, the size of the point estimates is also comparable with that study: the median 2SLS estimate obtained by Khandelwal is -0.58 for the price elasticity and 0.46 for the coefficient of the nest share.

Using the estimated parameters from the three models, we compute five different measures of quality. Our preferred measure is based on the estimates in column (1) and uses the expression for $\widetilde{\lambda}_{v,t}$ reported above. The first alternative measure is based as well on column (1), but excludes the residual from the expression of $\widetilde{\lambda}_{v,t}$. The second alternative uses the OLS estimates in column (2) and the original expression of $\widetilde{\lambda}_{v,t}$. The third alternative uses the estimates in column (3) and

[52] Bilateral distance is the population-weighted number of kilometers between the two countries' largest cities, and is sourced from CEPII. Oil prices are Brent prices. To compute product-level transportation costs, we start from variety-specific unit transportation costs for the US, which we construct using data from Feenstra et al. (2002). We regress these transportation costs on partner fixed effects, in order to remove the influence of distance from the US. We then take the average of the residuals across all partners within each 6-digit product code (recall that the HS and CN classifications coincide at that level of aggregation).

again employs the original expression for $\widetilde{\lambda}_{v,t}$. The last alternative is obtained as the residual from a regression of our preferred measure on product fixed effects, so as to further remove systematic differences in product and industry characteristics. We use these estimated $\widetilde{\lambda}_{v,t}$ to construct the variable $QNew$ as explained in the main text.

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Table 1 - Entry and Exit of Domestic Products, Imported Products and Imported Varieties

Entry	Exit
a) Domestic products	
4.99	4.81
b) Imported products	
1.18	0.76
c) Imported varieties: all	
13.23	10.47
d) Imported varieties: intermediate inputs	
13.09	10.58

Source: Prodcom and Comext. All figures are in percentage and are averaged across countries and years. Intermediate inputs are identified by mapping the CN classification into the BEC classification; see footnote 12 for details.

Table 2 - Decomposing Growth in Production and Import Value

Total	New	Exiting	Continuing
	a) Domestic production		
9.43	2.34	-1.56	8.65
100.00	*24.79*	*-16.51*	*91.72*
	b) Imports: products		
11.72	*0.15*	*-0.08*	*11.64*
100.00	*1.32*	*-0.69*	*99.37*
	c) Imports: varieties (all)		
11.72	*2.01*	*-1.25*	*10.96*
100.00	*17.13*	*-10.67*	*93.54*
	d) Imports: varieties (intermediate inputs)		
11.59	*2.31*	*-1.47*	*10.75*
100.00	*19.95*	*-12.69*	*92.74*

Source: Prodcom and Comext. All figures are in percentage and are averaged across countries and years. The decompositions are based on equation (1) in the text. See also the note to the previous table.

Table 3 - New Imported Inputs and Introduction of New Domestic Products

Dependent variable: Share of new products in total domestic products (*NP*)

	(1)	(2)	(3)	(4)
NII_{t-1}	0.122***	0.245***	0.404***	
	[0.018]	[0.028]	[0.050]	
$NIIov_{t-1}$				0.574***
				[0.065]
Obs.	33586	18256	4475	4619
R2	0.07	0.07	0.11	0.11
Industry aggregation	Nace 4	Nace 3	Nace 2	Nace 2
Estimation method	OLS	OLS	OLS	OLS

NII is the ratio of new over total imported varieties of intermediate inputs within each industry. *NIIov* is the ratio of new over total imported varieties of intermediate inputs from all industries; it is constructed as the weighted average of *NII* across all industries, using country-specific Import Matrix coefficients (see equation (3) in the text for details). All specifications control for country-industry and time effects. Standard errors are corrected for clustering within country-industry pairs. ***, **, * = indicate significance at 1, 5 and 10%, respectively.

Table 4 - Accounting for Outliers

Dependent variable: Share of new products in total domestic products (*NP*)

	Trimming (1%)	Winsorizing (1%)	Excluding industries with extreme values of *NP* or *NIIov*	Excluding countries with extreme values of *NP* or *NIIov*	Outliers-robust estimation procedure
	(1)	(2)	(3)	(4)	(5)
$NIIov_{t-1}$	0.623***	0.584***	0.659***	0.553***	0.518***
	[0.080]	[0.065]	[0.075]	[0.075]	[0.044]
Obs.	3079	4619	4156	3855	4619
R2	0.13	0.12	0.13	0.12	0.11

In all specifications, the level of industry aggregation is NACE 2. Column (1) excludes the observations at the bottom and top 1% of the distribution of *NP* and *NIIov*. Column (2) replaces those observations with the value of the first and last percentile. Columns (3) and (4) exclude, respectively, industries and countries with the highest and lowest average value of *NP* and *NIIov*: NACE 16, 19 and 23 in column (3); Germany, UK, Latvia and Lithuania in column (4). The results in column (5) are obtained using the *rreg* routine in Stata. All specifications control for country-industry and time effects. In columns (1)-(4), standard errors are corrected for clustering within country-industry pairs. ***, **, * = indicate significance at 1, 5 and 10%, respectively. See also notes to previous tables.

Table 5 - Using Alternative Definitions of the Regressor

Dependent variable: Share of new products in total domestic products (*NP*)

	Coeff.	Std. Err.	Obs.	R2
a) Using average weights from Use matrices				
$NIIov_{t-1}$	0.578***	[0.067]	4682	0.11
b) Using yearly weights from Use matrices				
$NIIov_{t-1}$	0.586***	[0.066]	4043	0.12
c) Excluding capital goods				
$NIIov_{t-1}$	0.541***	[0.063]	4619	0.11
d) Excluding also fuel and lubrificants				
$NIIov_{t-1}$	0.513***	[0.063]	4619	0.11

Each panel corresponds to a separate regression and all specifications control for country-industry and time effects. Standard errors are corrected for clustering within country-industry pairs. ***, **, * = indicate significance at 1, 5 and 10%, respectively. See also notes to previous tables.

Table 6 - Addressing Concerns with the Dependent Variable

Dependent variable: Share of new products in total domestic products (*NP*)

	Coeff.	Std. Err.	Obs.	R2
a) Considering only product codes that are present in the PC classification for the whole sample period				
$NIIov_{t-1}$	0.510***	[0.065]	4576	0.15
b) Excluding the first year of observations for each country				
$NIIov_{t-1}$	0.657***	[0.081]	4236	0.10
c) Excluding the first two years of observations for each country				
$NIIov_{t-1}$	0.337***	[0.070]	3793	0.08
d) Excluding the first three years of observations for each country				
$NIIov_{t-1}$	0.307***	[0.072]	3311	0.09

Each panel corresponds to a separate regression and all specifications control for country-industry and time effects. Standard errors are corrected for clustering within country-industry pairs. ***, **, * = indicate significance at 1, 5 and 10%, respectively. See also notes to previous tables.

Table 7 - Constructing Variables Using Values

Dependent variable: Share of new products in total domestic products (column (1)) or production value (columns (2)-(3))

	(1)	(2)	(3)
$NIIov_{t-1}$	0.547***	0.773***	1.148***
	[0.185]	[0.132]	[0.427]
Obs.	4619	2683	2683
R2	0.09	0.11	0.09
Dependent variable (*NP*) in	Numbers	Values	Values
Explanatory variable (*NIIov*) in	Values	Numbers	Values

The dependent variable (*NP*) is constructed using the number of domestic products in column (1), and their value in columns (2)-(3). The explanatory variable (*NIIov*) is constructed using the value of imported inputs in column (1) and (3), and their number in column (2). All specifications control for country-industry and time effects. Standard errors are corrected for clustering within country-industry pairs. ***, **, * = indicate significance at 1, 5 and 10%, respectively.

Table 8 - Adding Controls for Industry and Country Characteristics

Dependent variable: Share of new products in total domestic products (*NP*)

Industry-level controls	(1)	(2)	(3)	Country-level controls	(4)	(5)
$NIIov_{t-1}$	0.401***	0.391***	0.622***	$NIIov_{t-1}$	0.411***	0.174**
	[0.057]	[0.069]	[0.071]		[0.068]	[0.087]
$\ln KINT_{t-1}$	0.009	0.022*		$\ln GDP_{t-1}$	-0.281***	
	[0.008]	[0.011]			[0.052]	
$\ln MINT_{t-1}$	-0.006	0.029		$GDPGR_{t-1}$	1.151***	
	[0.019]	[0.025]			[0.230]	
$\ln LPROD_{t-1}$	0.001	-0.023		$\ln POP_{t-1}$	2.016***	
	[0.021]	[0.030]			[0.275]	
$\ln EMPL_{t-1}$	-0.013	0.006		$\ln EXCH_{t-1}$	0.169***	
	[0.018]	[0.021]			[0.043]	
$\ln IMPINT_{t-1}$		0.025*		$TGDP_{t-1}$	0.075***	
		[0.014]			[0.027]	
$TECH_{t-1}$		0.05		$KGDP_{t-1}$	-0.668***	
		[0.067]			[0.172]	
Obs.	4381	3266	4619	Obs.	4098	4619
R2	0.10	0.11	0.31	R2	0.15	0.53

KINT is capital intensity (capital expenditure per employee), *MINT* is material intensity (materials expenditure per employee), *LPROD* is labor productivity (value added per worker), *EMPL* is employment (number of employees), *IMPINT* is import penetration (imports over the sum of imports plus output), *TECH* is a proxy for technical change (high-tech share of capital investment). *GDP* is per capita GDP, *GDPGR* is per capita GDP growth, *POP* is population, *EXCH* is the real exchange rate, *TGDP* is the ratio of merchandise trade to GDP, and *KGDP* is the ratio of gross fixed capital formation to GDP. All specifications control for country-industry and time effects (except columns (3) and (5), which replace the time effects with, respectively, industry-time and country-time effects). Standard errors are corrected for clustering within country-industry pairs. ***, **, * = indicate significance at 1, 5 and 10%, respectively. See also notes to previous tables.

Table 9 - Controlling for Entry and Exit of Inputs and Products

Dependent variable: Share of new products in total domestic products (*NP*)

	(1)	(2)	(3)	(4)	(5)	(6)
$NIIov_{t-1}$	0.661***	0.556***	0.574***	0.666***	0.570***	0.521***
	[0.085]	[0.066]	[0.068]	[0.088]	[0.064]	[0.085]
NDI_{t-1}	0.076***					
	[0.020]					
IIV_{t-1}		-0.134*				
		[0.079]				
IIN_{t-1}			0.009			
			[0.243]			
$EXDI_{t-1}$				-0.083		
				[0.070]		
$EXII_{t-1}$				0.080		
				[0.094]		
EXP_{t-1}					-0.036	
					[0.025]	
NFG_{t-1}						0.067
						[0.083]
Obs.	4148	4619	4619	4152	4584	4619
R2	0.11	0.11	0.11	0.10	0.12	0.11

NDI is the share of new over total domestic inputs, constructed using average weights from the Use Matrices. *IIV* and *IIN* are the shares of imported inputs in, respectively, total import value and total number of imported varieties, both weigthed by average Import Matrix coefficients. *EXDI* and *EXII* are the shares of exiting inputs in the total number of domestic and imported intermediates, respectively; they are constructed using average weights from the Use and Import Matrices. *EXP* is the share of exiting products in the total number of products. *NFG* is the share of new over total imported varieties of final goods, constructed using average weights from the Import Matrices. All specifications control for country-industry and time effects. Standard errors are corrected for clustering within country-industry pairs. ***, **, * = indicate significance at 1, 5 and 10%, respectively. See also notes to previous tables.

Table 10 - Using Alternative Lags

Dependent variable: Share of new products in total domestic products (*NP*)

	Coeff.	Std. Err.	Obs.	R2
a) Current period				
$NIIov_{t}$	0.507***	[0.070]	4661	0.10
b) First lag				
$NIIov_{t-1}$	0.574***	[0.065]	4619	0.11
c) Second lag				
$NIIov_{t-2}$	0.697***	[0.069]	4490	0.14
d) Third lag				
$NIIov_{t-3}$	0.400***	[0.071]	4274	0.11
e) Fourth lag				
$NIIov_{t-4}$	0.047	[0.036]	4020	0.11
f) Fifth lag				
$NIIov_{t-5}$	0.005	[0.049]	3767	0.11

Each panel corresponds to a separate regression and all specifications control for country-industry and time effects. Standard errors are corrected for clustering within country-industry pairs. ***, **, * = indicate significance at 1, 5 and 10%, respectively. See also notes to previous tables.

Table 11 - Exploring Heterogeneity

Dependent variable: Share of new products in total domestic products (*NP*)

	EU15 vs. New EU Members	Countries with weak vs. strong product market regulation (PMR)	Imports from OECD vs. non-OECD countries
	(1)	(2)	(3)
$NIIov_{t-1}$	0.264***	0.271***	
	[0.062]	[0.071]	
$NIIov_{t-1}$ * Indic for New EU Members	0.488***		
	[0.109]		
$NIIov_{t-1}$ * Indic for countries with weak PMR		0.084	
		[0.097]	
$NIIov_{t-1}$ (Imports from OECD countries)			0.636***
			[0.115]
$NIIov_{t-1}$ (Imports from non-OECD countries)			0.417**
			[0.178]
Obs.	4619	4214	4619
R2	0.12	0.10	0.11

In column (1), *NIIov* is interacted with a dummy equal to 1 for the ten New EU Members. In column (2), it is interacted with a dummy equal to 1 for countries with weak product market regulation (i.e., countries for which the corresponding OECD index, averaged across all available years, is below the sample median). In column (3), *NIIov* is split up in two separate regressors, corresponding to imports from OECD and non-OECD countries, respectively. All specifications control for country-industry and time effects. Standard errors are corrected for clustering within country-industry pairs. ***, **, * = indicate significance at 1, 5 and 10%, respectively. See also notes to previous tables.

Table 12 - Identification: Instrumental Variables Regressions

Dependent variable: Share of new products in total domestic products (*NP*)

	(1)	(2)	(3)	(4)	(5)	(6)
$NIIov_{t-1}$	0.973***	1.067***	0.835***	0.726***	1.163***	0.434***
	[0.099]	[0.124]	[0.133]	[0.111]	[0.120]	[0.151]
NP_{t-1}						0.033**
						[0.014]
Cragg-Donald *F*-statistic	326.7	908.9	653.5	762.3		
Hansen test (*p*-value)	0.15					0.34
Sargan test (*p*-value)						0.85
AR1 test (*p*-value)						0.00
AR2 test (*p*-value)						0.94
Number of instruments						24
Obs.	4613	4613	4613	4613	4619	4140
R2	0.10	0.09	0.11	0.11		
Log-Pseudolikelihood					9497.03	
Estimation method	2SLS	2SLS	2SLS	2SLS	IV Tobit	SYS-GMM

In columns (1), (5) and (6), the exogenous instruments are the sixth lags of US input tariffs and imported inputs, computed for all trading partners in the world except the relevant EU country. In column (2), the only exogenous instrument is US input tariffs, whereas in column (3) it is US imported inputs. In column (4), the exogenous instrument is a shift-share instrument, constructed as explained in the text. Except for column (5), all specifications control for country-industry and time effects. Column (5) only controls for time effects. Standard errors are corrected for clustering within country-industry pairs, except in column (6) where they are adjusted using Windmeijer's (2005) finite-sample correction. ***, **, * = indicate significance at 1, 5 and 10%, respectively. See also notes to previous tables.

Table 13 - Identification: Trade Shocks

Dependent variable: Share of new products in total domestic products (*NP*)

	(1)	(2)	(3)	(4)	(5)
$NIIov_{t-1}$ (Imports from New WTO Members)	0.897***				
	[0.097]				
$NIIov_{t-1}$ (Imports from China)		1.052***			
		[0.130]			
$NIIov_{t-1}$ (Imports of inputs with large tariff cuts)			0.967***		
			[0.203]		
$NIIov_{t-1}$				0.109	-0.417
				[0.083]	[0.412]
$NIIov_{t-1}$ * Indic for Euro adoption				0.461***	
				[0.095]	
$NIIov_{t-1}$ * Indic for EU accession					0.807***
					[0.143]
Cragg-Donald *F*-statistic	37.63	16.04	180.00		
Hansen test (*p*-value)	0.22	0.55			
Obs.	4613	4613	4613	2726	1156
R2	0.004	0.04	0.045	0.12	0.24
Estimation method	2SLS	2SLS	2SLS	OLS	OLS

In column (1), the exogenous instruments are the sixth lags of US input tariffs and imported inputs from the New WTO Members (35 countries in total). In column (2), the exogenous instruments are the sixth lags of US input tariffs and imported inputs from China. In colum (3), the exogenous instrument is the sixth lag of US imported inputs, constructed using only inputs with large tariff cuts. In column (4), the estimation sample is restricted to countries that have adopted the Euro in 1999 or 2000. In column (5), the estimation sample is restricted to countries that have joined the EU in 2004 or 2007. All specifications control for country-industry and time effects. Standard errors are corrected for clustering within country-industry pairs. ***, **, * = indicate significance at 1, 5 and 10%, respectively. See also notes to previous tables.

Table 14 - New Imported Inputs and Introduction of New Domestic Products: Channels

Dependent variable: Share of new products in total domestic products (*NP*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Estimates							
$NIIov_{t-1}$	0.748***	0.385**	0.010	0.013	0.095	0.010	0.021
	[0.137]	[0.175]	[0.208]	[0.208]	[0.210]	[0.201]	[0.205]
		[0.150]	[0.181]	[0.182]	[0.189]	[0.180]	[0.182]
$NIIov_{t-1}$ * $PNew_{t-1}$		0.312*	-1.207***	-1.168***	-0.806***	-1.059***	-1.068**
		[0.196]	[0.330]	[0.324]	[0.312]	[0.283]	[0.477]
		[0.181]	[0.346]	[0.341]	[0.303]	[0.289]	[0.538]
$PNew_{t-1}$		-0.037	0.120***	0.117***	0.080**	0.107***	-0.195***
		[0.028]	[0.038]	[0.037]	[0.036]	[0.034]	[0.077]
		[0.026]	[0.038]	[0.038]	[0.034]	[0.034]	[0.074]
$NIIov_{t-1}$ * $QNew_{t-1}$			2.015***	1.966***	1.501***	1.857***	1.877***
			[0.496]	[0.488]	[0.465]	[0.437]	[0.599]
			[0.468]	[0.461]	[0.413]	[0.402]	[0.620]
$QNew_{t-1}$			-0.213***	-0.210***	-0.165***	-0.202***	0.099
			[0.064]	[0.063]	[0.061]	[0.057]	[0.057]
			[0.057]	[0.056]	[0.054]	[0.052]	[0.062]
Obs.	4,262	4,262	4,262	4,262	4,262	4,262	4,262
R2	0.09	0.12	0.13	0.13	0.12	0.13	0.12
Estimated quality	None	None	2SLS, imported inputs subsample	2SLS, imported inputs subsample, no residuals	OLS, imported inputs subsample	2SLS, whole sample of imported varieties	2SLS, imported inputs subsample, no product effects
Partial derivatives with respect to:							
NIIov							
Average			0.650***	0.647***	0.673***	0.650***	0.649***
			[0.067]	[0.068]	[0.074]	[0.064]	[0.066]
10th percentile			0.403***	0.403***	0.507***	0.434***	0.487***
			[0.087]	[0.075]	[0.072]	[0.064]	[0.105]
25th percentile			0.538***	0.542***	0.613***	0.548***	0.595***
			[0.058]	[0.064]	[0.063]	[0.060]	[0.060]
Median			0.674***	0.668***	0.690***	0.666***	0.666***
			[0.070]	[0.066]	[0.073]	[0.070]	[0.065]
75th percentile			0.771***	0.766***	0.756***	0.758***	0.731***
			[0.082]	[0.080]	[0.083]	[0.078]	[0.074]
90th percentile			0.857***	0.849***	0.807***	0.840***	0.785***
			[0.098]	[0.097]	[0.092]	[0.092]	[0.084]
QNew							
Average			0.067***	0.063***	0.043**	0.055***	0.065***
			[0.020]	[0.020]	[0.021]	[0.018]	[0.022]
PNew							
Average			-0.048***	-0.045**	-0.031*	-0.040**	-0.049*
			[0.018]	[0.018]	[0.017]	[0.017]	[0.026]

Column (1) estimates the baseline specification (see Table 3, column (4)) on the subsample with non-missing values for *PNew* and *QNew*, which are the relative price and relative quality of new imported inputs, in each country, industry and year. The quality estimates used to construct *QNew* are obtained by estimating equation (10), separately for each country and 4-digit NACE industry, and then adding up the variety fixed effect, the time fixed effect and the residuals from those regressions (except in column (4) where the residuals are excluded). The estimation of quality is performed by 2SLS in columns (3)-(4) and (6)-(7), and by OLS in column (5). Finally, the estimation of quality is performed on the subsample of imported input varieties, except in column (6) where it is performed on the whole sample of imported varieties (i.e., including also the final goods). In column (7), *PNew* and *QNew* are obtained after removing product fixed effects from prices and estimated qualities. All specifications in the table control for country-industry and time effects. The first standard error is bootstrapped (100 replications), the second is analytical and corrected for clustering within country-industry pairs. The standard errors of the derivatives are computed using the bootstrapped standard errors of the parameters. ***, **, * = indicate significance at 1, 5 and 10%, respectively. See also notes to previous tables.

Table 15 - New Imported Inputs and the Volume and Price of New Domestic Products

Dependent variables indicated in panels' headings

	Dep. Var.: Log volume				Dep. Var.: Log price			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
New_t	-0.742***	-0.697***	-0.647***	-0.674***	0.041**	0.039**	-0.047	-0.037
	[0.041]	[0.043]	[0.100]	[0.107]	[0.016]	[0.016]	[0.035]	[0.037]
$NIIov_{t-1}$ * New_t			-0.672	-0.081			0.717***	0.612**
			[0.737]	[0.787]			[0.252]	[0.263]
Obs.	180887	177288	177180	173614	180887	177288	177180	173614
R2	0.74	0.74	0.74	0.74	0.87	0.87	0.87	0.87

The results in columns (1), (2), (5) and (6) are obtained by estimating equation (8), those in columns (3), (4), (7) and (8) by estimating equation (9) (the coefficients of the linear term of *NIIov* are not reported). *New* is a dummy for new products. Prices are unit values. Observations in the highest and lowest decile of the price distribution are excluded. Columns (2), (4), (6) and (8) exclude products that exit in period t+1. All specifications control for product and country-time effects. ***, **, * = indicate significance at 1, 5 and 10%, respectively. See also notes to previous tables.

Table 16 - Price and Quantity Differences Between New and Existing Exports

Dependent variables indicated in columns' headings

	Log Volume (1)	Log Price (2)	Log Volume (3)	Log Price (4)	Log Volume (5)	Log Price (6)
Indic for new exp $prod_t$	-1.016***	0.023***				
	[0.016]	[0.006]				
Indic for new exp var_t			-3.508***	0.015***		
			[0.006]	[0.001]		
Indic for new exp from EU to US_t					-0.794***	0.033*
					[0.036]	[0.019]
Obs.	1829244	1829244	2963697	2963697	91701	91701
R2	0.36	0.06	0.46	0.05	0.65	0.89
Estimation sample	Exported products	Exported products	Exported varieties	Exported varieties	Exports to US	Exports to US

Columns (1)-(4) use exports to all destinations, whereas columns (5) and (6) use exports to the US. Columns (1)-(4) control for product and country-time effects, columns (5) and (6) for product and time effects. Standard errors are corrected for clustering within country-product pairs. ***, **, * = indicate significance at 1, 5 and 10%, respectively. See also notes to previous tables.

Table 17 - Quality Premia for New Goods

Dependent variable: Estimated quality of US imported varieties from the EU

	(1)	(2)	(3)	(4)	(5)	(6)
Indic for new EU exp to US_t	0.038***	0.073***	-0.004	-0.033	-0.063	-0.010
	[0.014]	[0.020]	[0.005]	[0.037]	[0.072]	[0.020]
$NIIov_{t-1}$ * Indic for new EU exp to US_t				0.516**	0.997**	0.053
				[0.261]	[0.503]	[0.125]
Obs.	91701	48218	43483	83508	42333	41175
R2	0.16	0.14	0.41	0.16	0.14	0.38
Estimation sample	Exports to US	Exports to US, long-ladder products	Exports to US, short-ladder products	Exports to US	Exports to US, long-ladder products	Exports to US, short-ladder products

The dependent variable is normalized to have zero mean and unitary variance. Quality estimates are retrieved from Khandelwal (2010). All regressions use the median value of these estimates by parter, year and 6-digit HS code. Only products with unique unit of measurement are used. Long-ladder products are products with ladder length above the sample median (ladder length is retrieved from Khandelwal, 2010). All columns control for product and time effects and standard errors are bootstrapped (100 replications). ***, **, * = indicate significance at 1, 5 and 10%, respectively. See also notes to previous tables.

Table A1 - Summary Statistics on Quality Estimates

	(1)	(2)	(3)
Coefficient of price	-0.805	-0.192	-0.774
Coefficient of nest share	0.441	0.868	0.489
Observations per estimation	1651	1651	1959
Varieties per estimation	460	460	552
Total number of estimations	3268	3268	4205
Total observations across all estimations	10235679	10235679	15137129
Sargan test (p-value)	0.15	-	0.09
Estimator and estimation sample	2SLS, imported inputs subsample	OLS, imported inputs subsample	2SLS, whole sample of imported varieties

Except for total number of estimations and total number of observations (fifth and sixth row), all figures are medians across countries and 4-digit industries. Column (1) refers to the model estimated by 2SLS on the subsample of imported input varieties. Column (2) refers to the model estimated by OLS on the same subsample. Column (3) refers to the model estimated by 2SLS on the whole sample of imported varieties (i.e., including also final goods).

Table A2 - Data Availability

Country	Production data	Trade data	Import matrices	Use matrices
Austria	1995-2007	1995-2007	1995, 2000, 2005	1995, 1997, 1999-2006
Belgium-Luxemburg	1995-2007	1988-2007	1995, 2000, 2005	1995, 1997, 1999-2005
Bulgaria	2001-2007	1999-2007		2000-2004
Czech Republic	2001-2007	1999-2007	2005	1995-2007
Denmark	1995-2007	1988-2007	1995, 2000-2006	1995-2006
Estonia	2000-2007	1999-2007	1997, 2000, 2005	1997, 2000-2006
Finland	1995-2007	1995-2007	1995-2007	1995-2007
Germany	1995-2007	1988-2007	1995, 2000-2006	1995, 1997-2006
France	1995-2007	1988-2007	1995, 1997, 1999-2006	1995, 1997-2006
Greece	1995-2007	1988-2007	2000, 2005	2000-2008
Hungary	2001-2007	1999-2007	1998, 2000, 2005	1998-2006
Ireland	1995-2007	1988-2007	1998, 2000, 2005	1998, 2000-2006
Italy	1995-2007	1988-2007	1995, 2000, 2005	1995-2006
Latvia	2001-2007	1999-2007	1996, 1998	1996, 1998, 2004
Lithuania	2000-2007	1999-2007	2000, 2005	2000-2006
Netherlands	1995-2007	1988-2007	1995-2002, 2004-2006	1995-2006
Poland	2002-2007	1999-2007	2000, 2005	2000-2005
Portugal	1995-2007	1988-2007	1995, 1999, 2005	1995-2006
Romania	2000-2007	1999-2007	2000, 2003-2006	2000, 2003-2006
Slovakia	1998-2007	1999-2007	2000, 2005	1995-2006
Slovenia	2001-2007	1999-2007	1996, 2000, 2001, 2005	1996, 2000-2006
Spain	1995-2007	1988-2007	1995, 2000, 2005	1995-2006
Sweden	1995-2007	1995-2007	1995, 2000, 2005	1995-2006
United Kingdom	1995-2007	1988-2007	1995	1995-2003