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"New Imported Inputs, Wages and Worker Mobility"

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Abstract

We provide a comprehensive assessment of the effects of new imported inputs on wage dynamics, on the skill-composition of the labor force, on worker mobility, and on the efficiency of matching between firms and workers. We employ matched employer-employee data for Italy, over 1995-2007. We complement these data with information on the arrival of new imported inputs at the industry level. We find new imported inputs to have a positive effect on average wage growth at the firm level. This effect is driven by two factors: (1) an increase in the white-collar/blue-collar ratio; and (2) an increase in the average wage growth of blue-collar workers, while the wage growth of white collars is not significantly affected. The individual-level analysis reveals that the increase in the average wage of blue collars is driven by the displacement of the lowest paid workers, while continuously employed individuals are not affected. We estimate the unobserved skills of workers following Abowd et al. (1999). We find evidence that new imported inputs lead to a positive selection of higher-skilled workers, and to an improvement in positive assortative matching between firms and workers.

JEL Classification: F14, F16.

Keywords: New imported inputs, wages, matched employer-employee data.

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1 Introduction

The most recent globalization wave has been characterized by an upsurge of trade in intermediate inputs (Feenstra, 1998; Feenstra and Hanson, 1999; Yi, 2003). This has been associated with a sizable increase in the number of new imported intermediates worldwide (Broda and Weinstein, 2006; Goldberg et al., 2009; Colantone and Crinò, 2014). A large literature has focused on the effects of foreign input sourcing. In particular, several studies have shown that imported inputs lead to productivity gains (Amiti and Konings, 2007, Halpern et al., 2015, Topalova and Khandelwal, 2011 and Yu, 2015); foster the introduction of new domestic products (Goldberg et al., 2010, and Colantone and Crinò, 2014); and improve export performance (Bas and Strauss-Kahn, 2014, and Bas and Strauss-Kahn, 2015). Much less attention has been paid to the effects of imported inputs on wages. In particular, only two studies, by Amiti and Davis (2011) and Chen et al. (2017), have found positive effects of lower input tariffs on, respectively, importing firms' wages in Indonesia, and firm-level skill premia in China.

In this paper, we employ a direct measure of the arrival of new imported inputs in Italy, at the industry level, and we provide the first comprehensive assessment of the effects of new imported inputs on wage dynamics, on the skill-composition of the labor force, on worker mobility, and on the efficiency of matching between firms and workers.

We use unique matched employer-employee data on the Italian manufacturing sector, sourced from the Italian Social Security Institute (INPS). We combine these data with information on the arrival of new imported inputs at the industry level, over the time-span 1995-2007. New imported inputs are identified based on disaggregated import data sourced from Eurostat. We find new imported inputs to have a positive impact on average wage growth at the firm level. This effect is driven by two factors: (1) an increase in the white-collar/blue-collar ratio; and (2) an increase in the average wage growth of blue-collar workers, while the wage growth of white collars is not significantly affected. The individual-level analysis reveals that the increase in the average wage of blue collars is driven by the displacement of the lowest paid workers. We instead find no impact of new imported inputs on the wages of continuously employed individuals, both for blue-collar and for white-collar workers. To further characterize the underlying adjustment process, we estimate the unobserved skills of workers following Abowd et al. (1999). We find evidence that new imported inputs lead to a positive selection of higher-skilled workers, and to an improvement in positive assortative matching between firms and workers.

Overall, our findings depict a picture of industry transformation driven by global sourcing opportunities. The arrival of new imported inputs determines a change in the composition of the workforce, with relatively more white collars employed in manufacturing firms, and a selection of the higher-wage and higher-skilled blue collars. In addition, there is a gain in terms of allocative efficiency, as the quality of matching between firms and workers improves. Our evidence is in line with earlier results on the positive effects of new imported inputs on domestic product innovation and export performance at the industry level (e.g., Colantone and Crinò, 2014 and Bas and Strauss-Kahn, 2014). In particular, we provide evidence that the effects we identify are stronger in industries characterized by higher product innovation rates and higher export intensity over the sample. These types of industry dynamics are indeed particularly consistent with the upgrade in the workforce uncovered by our analysis. Moreover, we also show that new imported imports have distinctive implications as compared to more general measures of offshoring.

For identifying new imported inputs, we rely on import data from the COMEXT database released by Eurostat. This provides information on yearly import flows for the universe of products –and from the universe of trading partners– at the highest possible level of disaggregation (8 digits). As in Colantone and Crinò (2014), new imported inputs are defined as new imported *varieties*, where a variety is a combination of a product-code and a partner-country. That is, we identify the first time in which a given input is imported in Italy from any country. Our identification procedure deals with the complications raised by changes in the classification of products over time, through the use of appropriate correspondence tables provided by Eurostat. Moreover, the entry of new inputs is not affected by discontinuities in imports, as any re-entry of a given variety after one or more years of break is not considered in our count of entries.

Our main variable of interest is the *overall* arrival rate of new imported inputs at the 2-digit NACE (Rev 1.1) industry level. For each given industry, this comprehensive measure includes new inputs that are imported not only within the industry itself, but also in other industries which are related through vertical linkages. To capture these linkages, we use information from the Eurostat Import Matrices, which reflect the weight of each industry in the total imports of intermediates of any other industry. Our overall entry rate of new imported inputs has an average value of about 11%, with a standard deviation of 3.2%. It ranges from a minumum of 4% to a maximum of 20%.

We address endogeneity concerns related to the arrival of new imported inputs in Italy using as instrument the arrival of new imported inputs in 24 other countries of the European Union, over the same period. To construct the instrumental variable, we first identify new imported inputs separately in each country, and then compute a country-industry specific entry rate for each year, exactly as done for Italy. Finally, we compute the average entry rate of new imported inputs across the 24 countries, for each industry and year. Inspired by earlier studies in the empirical trade literature (Autor et al., 2013; Dauth et al., 2014; Hummels et al., 2014; Bloom et al., 2016; Colantone et al., 2015), this instrument is meant to capture the variation in the arrival of new imported inputs that is driven by changes in supply conditions in foreign countries, and not by domestic industry-specific shocks in Italy, which might be endogenous to wage growth and worker mobility. Our results are robust to a large number of robustness checks on the IV-strategy, including controls for industry-specific contemporaneous shocks and underlying trends.

The remaining of the paper is organized as follows. In Section 2 we review the related literature. In Section 3 we discuss the identification of new imported inputs, as well as the related endogeneity concerns, and the instrumental variable employed in the econometric analysis. In Section 4 we present the matched employer-employee data. In Section 5 we describe the firm-level results, while the worker-level evidence is presented in Section 6. Section 7 contains results on worker selection and positive assortative matching. Section 8 provides a comprehensive discussion of the results, along with suggestive evidence on the possible channels. Finally, Section 9 concludes.

2 Related literature

This paper is related to different strands of empirical studies. In particular, as mentioned in the introduction, our work speaks to the literature investigating the effects of imported inputs in the domestic economy. Starting from the seminal paper by Amiti and Konings (2007), which provided the first evidence of a causal link between reduced input tariffs and firm-level productivity growth in Indonesia, several studies have found consistent results in a number of different settings. In particular, Halpern et al., 2015, Topalova and Khandelwal (2011), and Yu (2015) have shown evidence of productivity gains stemming from lower input tariffs in Hungary, India, and China, respectively.

Other empirical studies have investigated the relation between imported inputs and product innovation. Specifically, Goldberg et al. (2010) show that lower input tariffs lead to an expansion of the produced product bundle at Indian firms, while Colantone and

Crinò (2014) identify a positive effect of new imported inputs on the introduction of new domestic products at the country level, focusing on 25 countries of the European Union. Bas and Strauss-Khan (2014, 2015) have investigated the relation between imported inputs and export performance. In particular, Bas and Strauss-Kahn (2014) detect a positive effect of imported inputs on the number of varieties exported by French firms, while Bas and Strauss-Kahn (2015) provide evidence of a positive link between reduced input tariffs, upgraded imported inputs, and an upgrade in the quality of exported products by Chinese firms.

Our paper is most closely related to Amiti and Davis (2011), who have provided the first evidence of a positive effect of reduced input tariffs on the wages paid by importing firms. In particular, they develop a theoretical model with heterogeneous firms and fair wages, where the profit gains stemming from improved access to foreign inputs are shared with workers at firms that use imported inputs. Empirical support for this theoretical result is found using firm-level data from Indonesia, encompassing the trade liberalization of the 90s. A more recent paper by Chen et al. (2017) finds a positive effect of lower input tariffs on the skill premia paid by Chinese firms. Such an effect is stronger for ordinary firms than for processing importers, and grows with the share of skilled workers within the firm.

We contribute to this literature by focusing on a direct measure of new imported inputs in a developed economy such as Italy, and by using matched employer-employee data to provide the first comprehensive assessment of the effects of new imported inputs on wage dynamics, on the skill-composition of the labor force, on worker mobility, and on the efficiency of matching between firms and workers.

3 New imported inputs

For the identification of new imported inputs, we proceed as in Colantone and Crinò (2014). We start from the Eurostat COMEXT database, which provides information on the value and volume of imports for the universe of manufacturing products, and from all trading partners in the world (i.e., about 200 countries). Data are provided at the disaggregated 8-digit level of the Combined Nomenclature (CN) classification, which contains more than 10,000 codes. This classification is linked to the NACE Rev 1.1. industry classification through appropriate correspondence tables provided by Eurostat. Our main variables of interest are computed at the NACE 2-digit industry level. Specifically, we employ import data on Italy to construct the main explanatory variable capturing the arrival of new imported inputs. Based on the same database, we also perform the identification of new imported inputs for 24 additional EU countries in order to compute our instrumental variables.[1] Detailed information on the time coverage by country is provided in Table A1 of Appendix A. For Italy, trade data span the period 1988-2007.

In order to identify intermediate inputs out of the whole set of imported products, we map the CN classification into the Broad Economic Categories (BEC) classification. We then define as inputs all the CN codes that belong to the following BEC categories: “parts and accessories” (BEC 42); “capital goods, except transport equipment” (BEC 41); “processed industrial supplies” (BEC 22); “industrial transport equipment” (BEC 521); “parts and accessories of transport equipment” (BEC 53); “processed fuels and lubricants” (BEC 32); “processed food and beverages for industry” (BEC 121). As also discussed by Colantone and Crinò (2014), this is a standard way of defining inputs, both in the empirical trade literature and in the computation of aggregate trade statistics (e.g., by Eurostat, OECD, and the United Nations). In the results section, we nevertheless as-

[1] Data for Belgium and Luxembourg are aggregated by Eurostat, so the two countries constitute a single unit of analysis.

sess the robustness of our main findings to adopting narrower definitions of inputs, excluding capital goods, fuels, and lubricants.

In our analysis, we treat each imported variety of inputs as a different input. A variety is defined as a product (h) - partner (n) combination. This approach is standard in the empirical trade literature (see, e.g., Broda and Weinstein, 2006; Goldberg et al., 2009; Goldberg et al., 2010; Colantone and Crinò, 2014). We then identify new imported inputs in terms of *new imported varieties*. Specifically, we define variety (v) as a new imported input when product (h) is imported from partner (n) for the first time.

The identification of new imported varieties is all but trivial, due to changes that occur on a yearly basis in the Combined Nomenclature classification. These changes can be of two types: (1) new products are added to the classification with corresponding new codes; or (2) some of the existing (old) product codes are converted into new product codes. The second type of changes are problematic for our purposes, as they reflect renaming of products rather than the entry of new products in the set of imports.

We keep track of all changes in the CN classification using year-to-year correspondence tables provided by Eurostat. We then identify variety v, imported into country c in year t, as new if either: (1) code h is introduced in the classification in year t and does not have any old code corresponding to it; or (2) code h is introduced in the classification in year t and has one or more old codes corresponding to it, but none of them was imported into country c from partner n in any previous year; or (3) code h is not new to the classification, but was not imported into country c from partner n in any previous year.[2] With this identification procedure, a variety can be counted as new only once. If a country stops importing a given variety in one year, and then resumes imports at any

[2]The Stata code that identifies new imported inputs works as follows. Consider input variety v, which is made up of code h, imported by country c from partner n in year t, but not in previous years. The program first checks for the existence of old codes corresponding to h. If there is none, variety v is directly identified as a new imported input. If instead one or more old codes exist, the program verifies that country c was not importing any of the old codes from partner n in all previous years. Only in that case variety v is identified as a new imported input. This routine runs in approximately two days for each EU country.

later stage, such a re-entry is not considered as an entry for our purposes. Overall, the identification of new imported inputs in our analysis is not affected by changes in the CN classification, nor by discontinuities in bilateral trade flows over time.

Our measure of new imported inputs includes both product codes that are imported for the very first time from any partner country, and new varieties of product codes that were already imported from one or more partner countries, and start being imported from an additional trading partner. This comprehensive approach is meant to capture all the potential effects stemming from different characteristics of the new imported varieties as compared to the old varieties, even for the same product code. For instance, Colantone and Crinò (2014) have shown that improvements in price-quality ratios brought about by new imported varieties have positive implications for product innovation. Nevertheless, we also probe the robustness of our main findings to using a narrower definition of new imported inputs, which only considers the very first time that a given input code is imported from any partner country.

3.1 Measurement

To build up the industry-specific indicator for the arrival of new imported inputs, we start from the following measure:

$$NII_{jt} = (new\ imported\ inputs)_{jt}/(total\ imported\ inputs)_{jt}, \tag{1}$$

where j indexes 2-digit NACE Rev 1.1 industries, and t years.

NII_{jt} is the ratio between new varieties of imported inputs and the total number of input varieties imported in each 2-digit industry. Its computation is based on the mapping of each 8-digit CN product code into a NACE industry. This measure captures the arrival of new imported inputs within each industry. Thus, it is an *horizontal* indicator for input entry. Yet, as a matter of fact, firms within each industry source their intermediates also from other industries, which creates *vertical* linkages. Hence, to capture more comprehensively the entry of new imported inputs which are relevant for the firms belonging to each industry, we compute the following indicator:

$$NIIov_{jt} = \sum_k \phi_{jk} \cdot NII_{kt}. \tag{2}$$

$NIIov_{jt}$ is an *overall* indicator for the arrival of new imported inputs that are relevant for firms in industry j. It is computed as a weighted average of the horizontal indicator of input entry in each 2-digit industry k, including j itself. Each industry gets a weight ϕ_{jk} which reflects the share of industry k out of the total value of intermediates that industry j is importing from abroad. This information is obtained from Eurostat Import Matrices, which are available at the NACE 2-digit level of disaggregation. In particular, we compute the share of each industry for all the available years, and then compute ϕ_{jk} as the average of the yearly figures (see Table A1 of Appendix A for full information).

$NIIov_{jt}$ has an average value of about 11%, with a standard deviation of 3.2%. It ranges from a minumum of 4% to a maximum of 20%. These figures refer to the period 1995-2007, which is the time span of the econometric analysis employing firm and worker-level data. Yet, it is important to stress how new imported inputs are always identified based on import data that go back to 1988. For instance, when we identify an input variety as new in 1995, we know that this was not imported in any previous year until 1988, which is the first year with available information. This corroborates the robustness of our analysis.

In the empirical section, we show that our main findings are robust to computing ϕ_{jk} using import weights from the first available year, or industry shares that are based on domestic Input-Output coefficients rather than import-specific figures. Finally, we also show results using the horizontal indicator for the arrival of new imported inputs, NII_{jt}, instead of the overall one, $NIIov_{jt}$. When we do that, all the findings are qualitatively unaffected, but the magnitudes of the effects are somewhat smaller, in line with the idea that the horizontal indicator does not capture the full spectrum of relevant imported inputs.

3.2 Endogeneity

Our main goal is investigating the impact of new imported inputs on wages and worker mobility. To this purpose we estimate, for instance, regressions of wage growth –at the firm or worker level– against the lagged overall arrival of new imported inputs in the corresponding industry: $NIIov_j$. Similar regressions are run with the individual probability of job separation as a dependent variable. Alternatively, the dependent variables can be industry-level measures of unobserved worker skills, as well as proxies for positive assortative matching between firms and workers within each industry.

A concern with our analysis is the possible endogeneity of the arrival of new imported inputs. Endogeneity might stem from two different sources. First, there could be an issue of reverse causality. For instance, an increase in domestic wages in Italy could push firms to start sourcing more new inputs from abroad, to improve the price-quality ratio of intermediates. This would lead to an upward bias in the OLS estimates of the $NIIov_{jt}$ coefficient. Second, there could be an omitted variables issue. This could be driven by unobserved shocks inducing a correlation between changes in wages and variations in new imported inputs, conditional on other controls. For instance, negative supply shocks in Italy may have a negative impact on wages and simultaneously lead to more new imported inputs, as domestic suppliers become less productive and competitive. This would induce a downward bias in the OLS estimates.

These concerns are mitigated by the fact that our specifications always control for year dummies, and either firm or worker-firm fixed effects, depending on the specific regression. Moreover, we also include several time-varying controls for worker, firm, and industry characteristics (see *infra*). In addition, we run instrumental variable regressions. In particular, we instrument the overall arrival of new imported inputs in industry j and year t in Italy ($NIIov_{jt}$) using the average corresponding industry-specific indicator computed in the same year across the remaining 24 EU countries in our sample. This instrument is meant to isolate variation in new imported inputs in Italy which is due to exogenous changes in supply conditions in the origin countries, and not to domestic specific shocks which might be endogenous to wages and worker mobility. This IV approach is similar in spirit to the one originally proposed by Autor et al. (2013) for instrumenting US imports from China, and has been employed in several other studies (e.g., Dauth et al., 2014; Hummels et al., 2014; Bloom et al., 2016; Colantone et al., 2015). In the empirical section, we discuss possible concerns with the exclusion restriction underlying our IV strategy, and we present a large number of robustness checks corroborating our main findings.

4 Matched employer-employee data

We use a matched employer-employee database released by the Italian Social Security Institute (INPS). This includes a random sample of 185,544 manufacturing workers, for whom we can track the employment history between 1995 and 2007. The sample includes all workers born on day 1 or 9 of any month in any year. For each individual, we have information on age, gender, yearly wage, occupation (blue collar vs. white collar), type of contract (part-time vs. full-time), number of weeks worked (full-time equivalent), and firm of employment in each year.[3]

[3] In our sample, each worker has one observation per year, corresponding to one worker-firm contract. In the original administrative data, there are a few cases in which the same employee displays more than one contract in the same year, with different firms. In those cases, we focus on the worker-firm observation recording the highest yearly wage.

Overall, our sample includes 66,578 firms with at least one sampled worker employed in any year. For each of these firms, we have information on firm age and the total number of employees, as well as the number of white collars and blue collars on yearly basis, along with their average wages. Importantly, all the firm-level data refer to the whole workforce of each firm, and not just to the restricted number of workers that are randomly included in the INPS sample. In other words: (1) for each sampled worker we have complete worker-level information; (2) for each firm in which at least one sampled worker is employed, we have firm-level information referring to the universe of employees. Finally, for each firm we know the industry of affiliation, at the NACE (Rev 1.1) 2-digit level of disaggregation. This allows us to attribute to each firm its industry-specific arrival of new imported inputs in each year.

Table 1 reports some descriptive statistics on the sample of workers. Age ranges between 15 and 64, with an average of 39.7. The mean tenure within the firm is equal to about 4.8, with a maximum of 13. The average real weakly wage is equal to 460.43 euros.[4] Nominal wages are deflated using the FOI index published by the Italian National Institute for Statistics (ISTAT). FOI is a consumption price index computed specifically for employees' families. The base year is 2007. The average wage is higher for white-collar than blue-collar workers: 573.74 vs. 415.66. The average wage growth over two years, which is our main variable of interest, is equal to 3.6% over the full sample of workers. It is higher for white collars (5.3%) than for blue collars (3%).[5]

Table 2 contains descriptive statistics on the firm-level variables. Firm age ranges between 0 and 89, with an average of about 17. The average total number of employees is equal to 54.86.[6] The average share of white collars out of total workers is equal to 26%,

[4]In all our analysis, the weakly wages of part-time workers are made fully comparable with respect to the weakly wages of full-time workers. This is done by dividing the overall yearly wage by the number of full-time-equivalent weeks worked.

[5]As in Macis and Schivardi (2016), we have dropped records in the first and last percentiles of the wage distributions.

[6]The total number of employees has a minimum of zero. This refers to single entrepreneurs working

and its average growth over two years is equal to 0.8%. The mean growth of average firm-level wages is equal to 2.1% over two years. Consistent with the worker-level data, wage growth is higher for white collars (2.9%) than for blue collars (1.6%).

Table 1: Worker-level data: descriptives

	Mean	Std. Dev.	Min	Max
Age	39.70	9.53	15	64
Tenure	4.78	3.16	1	13
Real average weekly wage: all	460.43	171.07	13.84	3401.45
Real average weekly wage: blue collars	415.66	112.98	13.84	3382.40
Real average weekly wage: white collars	573.74	223.28	17.46	3401.45
2-years growth of real wage: all	0.036	0.118	-0.565	0.616
2-years growth of real wage: blue collars	0.030	0.116	-0.565	0.616
2-years growth of real wage: white collars	0.053	0.122	-0.565	0.616

Table 2: Firm-level data: descriptives

	Mean	Std. Dev.	Min	Max
Age	16.68	10.52	0	89
Size (total number of employees)	54.86	314.19	0	72199
Share of white collars	0.26	0.18	0	1
2-years growth of share of white collars	0.008	0.053	-0.200	0.246
2-years growth of real annual wage: all	0.021	0.072	-0.248	0.275
2-years growth of real annual wage: blue collars	0.016	0.079	-0.363	0.346
2-years growth of real annual wage: white collars	0.029	0.138	-0.546	0.606

5 Firm-level evidence

5.1 Econometric specification

At the firm level, we estimate specifications of the following form:

$$Firm\ Outcome_{zjt} = \alpha_z + \alpha_t + \beta_1 NIIov_{jt-2} + \mathbf{F}_{zt-2}\gamma^{'} + \mathbf{S}_{jt-2}\lambda^{'} + \varepsilon_{zjt}, \tag{3}$$

where z indexes firms, j industries, and t years.

Depending on the regression, $Firm\ Outcome_{zjt}$ is, alternatively, the firm-level growth of: average wage; share of white collars out of total workers; average white collars wage;

at firms with no additional employees.

and average blue collars wage. All variables are measured at the firm (z) level, between year t and $t-2$. α_z and α_t are firm and year fixed effects, respectively. $NIIov_{jt-2}$ is the overall arrival rate of new imported inputs in industry j in year $t-2$. This variable is computed according to equation 2, taking into account vertical linkages across NACE 2-digit industries.[7]

$\mathbf{F}_{zt-2}$ is a vector of controls for firm characteristics in year $t-2$. It includes firm age and the logarithm of firm size, measured as the total number of employees.

$\mathbf{S}_{jt-2}$ is a vector of industry-level controls in year $t-2$. It includes five variables: (1) labor productivity, measured as value added per worker (in logs); (2) capital intensity, proxied by capital compensation per worker (in logs); (3) material intensity, proxied by materials expenditure per worker (in logs); (4) export intensity, measured as exports over output; and (5) import intensity, measured as imports over output. These controls are meant to account for cross-industry differences at the moment in which new imported inputs arrive. Data on labor productivity, capital, and material intensity are from the World Input-Output Database (WIOD, Timmer et al., 2015). Export and import intensity are constructed from Eurostat data; specifically, trade data are from COMEXT, while output data are sourced from Structural Business Statistics.

To summarize, our identification strategy consists of comparing changes in firm performance across initially similar firms, operating in initially similar industries, except for the arrival of new imported inputs.

5.2 Baseline results

Table 3 reports the baseline results at the firm level. The table has 12 columns, referring to three different groups of regressions. Specifically, in columns 1-4 we run OLS estima-

[7] We obtain very similar results if we employ the third or fourth lag of $NIIov$, changing the rest of the specification accordingly, e.g., computing wage growth between year t and $t-3$, or between year t and $t-4$. These results are available upon request.

tions of equation 3, including firm and year fixed effects, but excluding the two vectors of firm and industry controls ($\mathbf{F}_{zt-2}$ and $\mathbf{S}_{it-2}$). In columns 5-8, we estimate the same specification, but instrumenting $NIIov_{jt-2}$ using the arrival rate of new imported inputs in other EU countries. Finally, in columns 9-12 we add firm and industry controls to the IV regressions. In all cases, standard errors are clustered at the industry level, to account for possible correlation of errors across observations within industries.

For each group of regressions, the dependent variable in the first column is the growth of average wages at the firm level. This is followed by the growth in the share of white-collar workers out of total firm employment (second column); the growth of average wage for white collars within the firm (third column); and the growth of average wage for blue collars within the firm (fourth column). All these variables are measured between year t and $t-2$, that is, over two years after the arrival of new imported inputs in year $t-2$.

Across the board, results in Table 3 suggest that new imported inputs lead to higher growth of firm-level average wages. Such growth is driven by two factors: (1) an increase in the share of white collars out of total workers; and (2) an increase in the average wage of blue collars. Conversely, the average wage of white collar workers does not seem to be affected. Such findings are very similar across the three groups of regressions. In particular, OLS and IV estimates of the $NIIov$ coefficient are very close to each other, pointing to the absence of a clear endogeneity bias in any direction. This is consistent with our earlier discussion on the possible sources of endogeneity, which could bias OLS estimates both upwards and downwards, thus potentially compensating each other. In line with the expectations, the first-stage coefficient of the instrument is always positive and statistically significant. Moreover, the F-statistic is comfortably high, reassuring on the strength of the instrument.

In terms of magnitudes, the $NIIov$ coefficient in the baseline IV specification of column 9 indicates that a one-standard-deviation increase in the share of new imported inputs (i.e., by 3.2 percentage points) leads to an increase in the overall average wage growth by around 0.4%. This is far from negligible, considering that the average 2-year wage growth at the firm level is equal to 2%, with a standard deviation of 7.2%. A similar result is obtained in column 12 with respect to the growth of blue-collar average wages, whose 2-year growth is equal on average to 1.6% (std. dev. of 7.9%). Finally, according to column 10, the same one-standard-deviation increase in $NIIov$ leads to an increase in the growth of the white-collar share by 0.13%, which is equal to almost 16% of its average 2-year growth rate: 0.82%. By and large, the effects of new imported inputs appear to be not only statistically significant, but also economically meaningful.

Table 3: Firm-level results: baseline

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent Variable:	Δ wage All	Δ share WC	Δ wage WC	Δ wage BC	Δ wage All	Δ share WC	Δ wage WC	Δ wage BC	Δ wage All	Δ share WC	Δ wage WC	Δ wage BC
NIIov	0.131***	0.033***	0.048	0.134***	0.136***	0.039***	0.083	0.135***	0.126***	0.042***	0.052	0.129***
	[0.036]	[0.009]	[0.039]	[0.042]	[0.033]	[0.008]	[0.053]	[0.039]	[0.031]	[0.007]	[0.032]	[0.038]
Estimator	OLS	OLS	OLS	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Firm controls	no	no	no	no	no	no	no	no	yes	yes	yes	yes
Industry controls	no	no	no	no	no	no	no	no	yes	yes	yes	yes
Firm effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Obs.	415,519	415,519	415,519	415,519	415,519	415,519	415,519	415,519	415,490	415,490	415,490	415,490
R2	0.028	0.001	0.008	0.026	0.028	0.001	0.008	0.026	0.029	0.004	0.008	0.026
First-stage results												
New Imported Inputs EU	-	-	-	-	0.926***	0.926***	0.926***	0.926***	0.921***	0.921***	0.921***	0.921***
	-	-	-	-	[0.088]	[0.088]	[0.088]	[0.088]	[0.089]	[0.089]	[0.089]	[0.089]
Kleibergen-Paap F-Statistic	-	-	-	-	110.8	110.8	110.8	110.8	107.0	107.0	107.0	107.0

Standard errors are corrected for clustering within industries. ***, **, * = indicate significance at the 1, 5 and 10% level, respectively.

5.3 Robustness and sensitivity

In Tables 4-8, we submit our baseline results to a large number of robustness and sensitivity checks. All the reported results refer to IV estimations including firm and year fixed effects, as well as firm and industry-level controls, as in columns 9-12 of Table 3.

In panel (1), instead of using $NIIov$, we include as an explanatory variable the second lag of $NIIj$, which is the share of new imported input varieties out of the total number of imported varieties within industry j only, as defined in equation 1. Compared to $NIIov$, this variable thus excludes new imported varieties in other industries that supply inputs to industry j. The instrument is also computed accordingly. Results are in line with the baseline evidence of Table 3. If anything, the coefficients are somewhat smaller. This is consistent with the idea that firms in any industry source intermediates also from other industries; hence, the arrival of new imported inputs in related industries matters as well. Our baseline measure, $NIIov$, is meant to take into account all the new imported inputs that might be relevant.

In panel (2), we include in the specification the share of new domestic inputs. This variable is computed in two steps as in Colantone and Crinò (2014), based on Eurostat PRODCOM data. First, we identify all the new 8-digit products that start to be produced in each industry and year, and compute their ratio over the total number of products.[8] Second, we compute an overall measure of the entry of new domestic inputs by taking the weighted average of industry-specific entry rates as in equation 2, using year-specific weights from the domestic Input-Output matrices. The baseline results on $NIIov$ are unaffected, while we do not find any significant association between our firm-level outcomes and the entry of new domestic inputs. This evidence lines with earlier findings in the literature, where several studies have shown that imported inputs do have specific

[8]See Colantone and Crinò (2014) for a complete explanation of the identification of new domestic products.

implications that distinguish them from domestic inputs (e.g., Amiti and Konings, 2007; Colantone and Crinò, 2014).

A possible concern with our analysis is that international trade might have an impact on wages not only through the arrival of new imported inputs, but also through other factors. Our baseline specifications always control for both import and export intensity. On top of that, in panels (3) to (6) we investigate the robustness of our results to the inclusion of additional variables related to trade. Specifically, in panel (3) we include the share of new out of total imported varieties of final goods within each industry. The inclusion of this variable leaves our main findings unchanged. If anything, we find some evidence of a negative correlation between new imported final goods and wages. This is consistent with the presence of competition effects induced by imports of final goods, which might reduce wage growth at domestic firms (see, e.g. Autor et al., 2013).

Next, one could wonder whether our measure of new imported inputs is just picking up the role of offshoring more in general. To account for that, in panels (4)-(6) we include in the regressions three measures that are meant to capture offshoring in more general terms. In particular, in panel (4) we include the (log) value of imported inputs within the industry. In panel (5) we include the share of inputs out of total imports within the industry; while in panel (6) we introduce an overall value of such ratio across related industries, computed through Input-Output weights as done for $NIIov$ in equation 2. Our results on the role of new imported inputs are robust in all regressions. The coefficients of the new variables are always negative, and often significant, in line with a negative impact of offshoring on wages. Overall, this evidence suggests the new imported inputs might have very different implications than general offshoring.

Finally, in panels (7)-(9) we investigate whether the source of new imported inputs matters. Specifically, in panel (7) we reconstruct $NIIov$ focusing only on imported input varieties from the set of 52 low-income countries identified by Bernard et al. (2006).[9] In panel (8) we focus on all other trading partners of Italy, while in panel (9) we restrict to OECD countries only. The instruments are changed accordingly. Our results are robust across the board. In panels (7) and (9) we even find weak evidence of a positive effect on the average white-collar wage. These results suggest that new imported inputs might generate similar effects on wages regardless of their different sources. Even the magnitudes of the effects are very similar across panels if one takes into account the differences in standard deviations among the three versions of $NIIov$.[10] This evidence is in line with earlier theoretical findings by Colantone and Crinò (2014), who have highlighted two possible channels through which new imported inputs may work: (1) by expanding the set of available intermediates for domestic producers; and (2) by allowing access to better varieties of inputs in terms of price-quality ratios. Such effects might arise both as firms source cheaper inputs from low-income countries, and as they start sourcing more sophisticated inputs at better conditions from new suppliers in richer industrialized countries.

In Table 5 we focus on alternative measures of new imported inputs. We start by assessing the robustness of our results to changing the Input-Output weights that are employed in the computation of $NIIov$, as outlined in equation 2. Specifically, in panel (1) we use weights obtained from the import matrix in the first available year, rather than the average import weights across years used in the baseline measure of $NIIov$. The advantage of using first-year weights is that of capturing the structure of backward linkages at the beginning of the sample, although this measure might clearly be more noisy as compared to the baseline. In panel (2) we use year-specific weights obtained

[9]These countries are identified as having a level of GDP per capita lower than 5% of the US figure. The full list is available in Table A2 of Appendix A.

[10]In particular, $NIIov$ from low-income countries has an average of 1.1%, with a standard deviation of 0.26%. For other countries the average is 9.9%, with standard deviation of 2.85%. For OECD countries the average is 5.2%, with standard deviation of 2.16%.

Table 4: Robustness checks: additional variables

	(1)	(2)	(3)	(4)
Dependent Variable:	Δ wage All	Δ share WC	Δ wage WC	Δ wage BC
1) Only new imported inputs within the same industry				
NIIj	0.083***	0.021***	0.041	0.079***
	[0.020]	[0.007]	[0.027]	[0.025]
Obs.	415,371	415,371	415,371	415,371
R2	0.029	0.004	0.008	0.026
2) Including new domestic inputs				
NIIov	0.124***	0.038***	0.051	0.129***
	[0.031]	[0.010]	[0.033]	[0.038]
Share of new domestic inputs	0.075	0.006	-0.017	0.071
	[0.083]	[0.014]	[0.055]	[0.093]
Obs.	376,666	376,666	376,666	376,666
R2	0.029	0.005	0.007	0.027
3) Including new imported final goods				
NIIov	0.139***	0.042***	0.056	0.147***
	[0.030]	[0.007]	[0.035]	[0.038]
Share of new imported final goods	-0.088**	-0.002	-0.032	-0.117***
	[0.038]	[0.010]	[0.030]	[0.043]
Obs.	415,490	415,490	415,490	415,490
R2	0.029	0.004	0.008	0.026
4) Including overall value of imported inputs				
NIIov	0.101***	0.039***	0.034	0.105***
	[0.030]	[0.007]	[0.033]	[0.038]
ln(value of all imported inputs)	-0.020**	-0.002	-0.014**	-0.019**
	[0.008]	[0.002]	[0.006]	[0.009]
Obs.	415,371	415,371	415,371	415,371
R2	0.029	0.004	0.008	0.027
5) Controlling for share of inputs out of total imports				
NIIov	0.084**	0.032***	0.025	0.086*
	[0.035]	[0.009]	[0.038]	[0.045]
Share of inputs over total imports: same industry	-0.062	-0.015	-0.039	-0.065
	[0.043]	[0.011]	[0.030]	[0.046]
Obs.	415,490	415,490	415,490	415,490
R2	0.029	0.004	0.008	0.026
6) Controlling for share of inputs out of total imports				
NIIov	0.084**	0.033***	0.028	0.090**
	[0.034]	[0.008]	[0.038]	[0.044]
Share of inputs over total imports: overall	-0.132**	-0.028	-0.073**	-0.122
	[0.063]	[0.018]	[0.037]	[0.075]
Obs.	415,490	415,490	415,490	415,490
R2	0.029	0.004	0.008	0.027
7) Focus on inputs from low-income countries				
NIIov from low-income countries	1.532***	0.301**	0.461*	1.538***
	[0.258]	[0.118]	[0.278]	[0.301]
Obs.	415,490	415,490	415,490	415,490
R2	0.028	0.004	0.008	0.026
8) Focus on inputs from all other countries				
NIIov from all other countries	0.140***	0.048***	0.064	0.143***
	[0.038]	[0.008]	[0.040]	[0.046]
Obs.	415,490	415,490	415,490	415,490
R2	0.029	0.004	0.008	0.026
9) Focus on inputs from OECD countries				
NIIov from OECD countries	0.256***	0.085***	0.129*	0.263**
	[0.093]	[0.022]	[0.078]	[0.107]
Obs.	415,490	415,490	415,490	415,490
R2	0.029	0.004	0.008	0.026

Standard errors are corrected for clustering within industries.
***, **, * = indicate significance at the 1, 5 and 10% level, respectively.

from Use Matrices, which are informative of input-output linkages based on domestic transactions only. In panel (3) we instead use the average values of these weights over all years. Our results remain very stable across the three panels, in terms of size and significance.

One could wonder that our baseline measure of new imported inputs is noisy, as input varieties might exit shortly after their entry. To rule out that our results are driven by such short-run volatility of imports, in panel (4) we reconstruct $NIIov$ by including as new imported inputs only those varieties that keep being imported until the end of the sample after having entered in one year. All our baseline results are confirmed, and we also find evidence of a significant positive effect on the average wage of white collars. To further account for the churning of imported inputs, in panel (5) we include as an explanatory variable the net entry of imported input varieties. Finally, in panel (6), instead of considering all the new imported varieties (i.e., combinations of input codes and trading partners), when computing $NIIov$ we focus only on the very first imported variety of any input. None of these robustness checks alters our main results. Notably, when considering only the first varieties, the coefficients are somewhat smaller. This is suggestive of the importance of considering also new varieties of previously imported inputs, as changes in the source countries might entail relevant changes in input characteristics such as quality and prices, which do have implications on firm-level adjustments.

As a final robustness check on the computation of $NIIov$, in panel (7) we exclude capital goods, while in panel (8) we also exclude fuels and lubricants. Results are largely unaffected also in this case. If anything, we detect again some weak evidence of a positive effect of new imported inputs on the average wage of white collars.

In Table 6 we perform robustness checks related to the instrumental variable. The exclusion restriction behind our identification strategy is that, conditional on other covariates, the arrival of new imported inputs in other European countries is orthogonal to

Table 5: Robustness checks: alternative measures

	(1)	(2)	(3)	(4)
Dependent Variable:	Δ wage All	Δ share WC	Δ wage WC	Δ wage BC
1) Weights from first available Import Matrix				
NIIov	0.138***	0.045***	0.058*	0.140***
	[0.034]	[0.008]	[0.035]	[0.041]
Obs.	415,490	415,490	415,490	415,490
R2	0.029	0.004	0.008	0.026
2) Weights from Use Matrices (year-specific)				
NIIov	0.155***	0.044***	0.060	0.163***
	[0.035]	[0.007]	[0.037]	[0.044]
Obs.	415,490	415,490	415,490	415,490
R2	0.029	0.004	0.008	0.026
3) Weights from Use Matrices (average)				
NIIov	0.154***	0.042***	0.070	0.159***
	[0.035]	[0.009]	[0.043]	[0.045]
Obs.	415,490	415,490	415,490	415,490
R2	0.029	0.004	0.008	0.026
4) Only new inputs imported for all years after entry				
NIIov	1.148***	0.281***	0.520***	1.173***
	[0.310]	[0.058]	[0.180]	[0.365]
Obs.	415,490	415,490	415,490	415,490
R2	0.028	0.004	0.008	0.026
5) Net entry				
NIIov	0.058***	0.015***	0.022	0.067***
	[0.021]	[0.006]	[0.015]	[0.023]
Obs.	415,490	415,490	415,490	415,490
R2	0.029	0.004	0.008	0.026
6) Only first varieties				
Net entry of imported inputs	0.086***	0.030***	0.023	0.091***
	[0.021]	[0.005]	[0.017]	[0.026]
Obs.	415,490	415,490	415,490	415,490
R2	0.029	0.004	0.008	0.026
7) Excluding capital goods				
NIIov	0.108***	0.042***	0.053*	0.101***
	[0.030]	[0.006]	[0.027]	[0.038]
Obs.	415,490	415,490	415,490	415,490
R2	0.029	0.004	0.008	0.026
8) Excluding capital goods, fuels, and lubricants				
NIIov	0.101***	0.041***	0.047*	0.092**
	[0.031]	[0.006]	[0.025]	[0.039]
Obs.	415,490	415,490	415,490	415,490
R2	0.029	0.004	0.008	0.026

Standard errors are corrected for clustering within industries.
***, **, * = indicate significance at the 1, 5 and 10% level, respectively.

firm-specific shocks occurring in Italy. We believe this is a plausible assumption, given that our baseline specifications include firm and year fixed effects, as well as several firm and industry controls. Nevertheless, in what follows we show that our main results are robust to a number alternative IV approaches, which are meant to address any potential remaining correlation between the instrument and the error term. In particular, since one could worry about endogeneity issues introduced by correlated demand and supply shocks across countries, we employ alternative instruments that respond to these concerns.

In panel (1), we exclude from the computation of the instrument the arrival of new imported inputs in France and Germany. These are the main trading partners of Italy in Europe, leading to higher cross-country correlation in the business cycle than with other EU members (Artis et al., 2004). This might have potential implications for the exogeneity of the instrument. The exclusion of France and Germany from the instrumental variable does not lead to any significant changes in our results. The same applies to panel (2), where we instrument the arrival of new imported inputs in Italy focusing exclusively on new imported inputs in the UK, a country whose business cycle is actually more correlated with the US than with continental Europe, also due to the fact that the UK never adopted the Euro as its currency (Artis et al., 2004).

In the same vein, in panel (4) we compute the instrument by considering only 10 countries of Central and Eastern Europe that entered the EU between 2004 and 2007.[11] Over our period of analysis, 1995-2007, these countries witnessed a process of transition and convergence towards the rest of Europe. These economic trajectories were very different than those of Italy: an older industrialized member of the EU. Moreover, none of the accession countries adopted the Euro over the sample period, with the only exception of Slovenia in 2007. This very conservative choice on the construction of the

[11] These countries are: Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Romania, Poland, Slovakia, Slovenia.

instrument leads unsurprisingly to a lower F-statistic in the first stage. Even then, our main results on wages are confirmed, while the $NIIov$ coefficient in the second column is positive but not statistically significant.

In panels (4) to (6), in line with Autor et al. (2013) and Colantone and Crinò (2014), we exclude from the analysis three groups of industries for which correlated shocks across countries are more likely to be relevant. Specifically, in panel (4) we exclude the most cyclical industries, identified as the ones witnessing the highest correlation between their own output growth and GDP growth in Italy over the sample.[12] In panel (5), we exclude a number of industries characterized by significant global fluctuations in the period of analysis, as identified by Autor et al. (2013).[13] Finally, in panel (5) we exclude the most energy intensive industries, as identified by the US Department of Energy.[14] Our main results are robust across the board. If anything, we tend to find a significant positive effect of new imported inputs also on the white-collar wages. Moreover, the estimated coefficients tend to be larger than in the baseline regressions, which therefore seem to provide conservative estimates of the effects of new imported inputs.

In Table 7 we augment the baseline specifications with different sets of fixed effects capturing time trends. These are meant to absorb remaining contemporaneous shocks, thus further raising confidence in the validity of the exclusion restriction. In particular, following Colantone and Crinò (2014), we include in the regressions *sector*-year dummies, where sectors are defined as groups of 2-digit industries witnessing similar dynamics over the sample in terms of some observable outcomes. For instance, in panel (1) we focus on the growth in import intensity between 1995 and 2007. We measure

[12] These industries are: "apparel" (NACE 18); "pulp and paper" (NACE 21); "coke, petroleum products, and nuclear fuel" (NACE 23); "non-metallic mineral products" (NACE 26); and "automotive" (NACE 34).

[13] These industries are: "textiles" (NACE 17); "apparel" (NACE 18); "leather" (NACE 19); "non-metallic mineral products" (NACE 26); "basic metals" (NACE 27); and "office machinery and computers" (NACE 30).

[14] These industries are: "pulp and paper" (NACE 21); "coke, petroleum products, and nuclear fuel" (NACE 23); "chemicals" (NACE 24); "non-metallic mineral products" (NACE 26); and "basic metals" (NACE 27).

Table 6: Robustness checks: alternative instruments

	(1)	(2)	(3)	(4)
Dependent Variable:	Δ wage All	Δ share WC	Δ wage WC	Δ wage BC
1) Excluding France and Germany				
NIIov	0.122***	0.043***	0.051	0.125***
	[0.033]	[0.007]	[0.034]	[0.040]
Obs.	415,490	415,490	415,490	415,490
R2	0.029	0.004	0.008	0.026
First stage coefficient	0.908***	0.908***	0.908***	0.908***
	[0.102]	[0.102]	[0.102]	[0.102]
Kleibergen-Paap F-Statistic	78.92	78.92	78.92	78.92
2) Focusing on UK only				
NIIov	0.144***	0.037***	0.028	0.154***
	[0.033]	[0.010]	[0.024]	[0.036]
Obs.	415,490	415,490	415,490	415,490
R2	0.029	0.004	0.008	0.026
First stage coefficient	0.827***	0.827***	0.827***	0.827***
	[0.043]	[0.043]	[0.043]	[0.043]
Kleibergen-Paap F-Statistic	365.5	365.5	365.5	365.5
3) Focusing on 10 Central Eastern EU new Members				
NIIov	0.148**	0.016	0.098	0.195**
	[0.068]	[0.022]	[0.078]	[0.082]
Obs.	225,918	225,918	225,918	225,918
R2	0.017	0.007	0.002	0.016
First stage coefficient	0.781***	0.781***	0.781***	0.781***
	[0.268]	[0.268]	[0.268]	[0.268]
Kleibergen-Paap F-Statistic	8.48	8.48	8.48	8.48
4) Excluding most cyclical industries				
NIIov	0.144***	0.048***	0.050*	0.153***
	[0.031]	[0.006]	[0.027]	[0.039]
Obs.	354,811	354,811	354,811	354,811
R2	0.03	0.004	0.009	0.027
First stage coefficient	0.958***	0.958***	0.958***	0.958***
	[0.076]	[0.076]	[0.076]	[0.076]
Kleibergen-Paap F-Statistic	158.67	158.67	158.67	158.67
5) Excluding most volatile industries (Autor et al., 2013)				
NIIov	0.166**	0.018	0.142**	0.200**
	[0.070]	[0.022]	[0.060]	[0.085]
Obs.	315,309	315,309	315,309	315,309
R2	0.031	0.004	0.009	0.028
First stage coefficient	0.845***	0.845***	0.845***	0.845***
	[0.056]	[0.056]	[0.056]	[0.056]
Kleibergen-Paap F-Statistic	223.54	223.54	223.54	223.54
6) Excluding most energy-intensive industries				
NIIov	0.143***	0.048***	0.054*	0.148***
	[0.033]	[0.006]	[0.029]	[0.040]
Obs.	353,453	353,453	353,453	353,453
R2	0.028	0.004	0.008	0.026
First stage coefficient	0.934***	0.934***	0.934***	0.934***
	[0.091]	[0.091]	[0.091]	[0.091]
Kleibergen-Paap F-Statistic	106.07	106.07	106.07	106.07

Standard errors are corrected for clustering within industries.
***, **, * = indicate significance at the 1, 5 and 10% level, respectively.

this growth for each 2-digit industry, and then we aggregate industries in five equal-size groups, each referring to a bin of the distribution. Each group of industries is a *sector*. The regressions include the full set of interactions between the five dummies identifying each sector and the year dummies. These interactions capture all time-varying differences across industries belonging to each sector. This implies that we identify the effect of new imported inputs only out of remaining variation, within years, across industries that witness similar dynamics of import competition over the sample. In panel (2), we repeat the same exercise considering changes in export intensity. In panel (3) the focus is on output growth, while in panels (4) and (5) the groups of similar industries are identified based on capital and material intensity growth, respectively. Overall, the idea is that industries witnessing similar dynamics of these variables might have been exposed to similar shocks over time. All results are in line with our baseline evidence, in terms of magnitude and significance.

Finally, in Table 8 we allow for heterogeneous trends across industries, based on pre-sample performance. For instance, in panel (1) we measure the growth in import intensity between 1990 and 1995 –thus over five years before the beginning of the sample period– and we interact it with year dummies. This allows for differential trajectories over time across industries, based on their ex-ante growth in import pressure. In panel (2), we repeat the same analysis focusing on pre-sample growth of export intensity. In panel (3) we consider output growth, while in panels (4) and (5) we focus on capital and material intensity, respectively. In all cases, our evidence is essentially unaffected. If anything, also in this type of analysis we sometimes find evidence of a positive effect of new imported inputs on white-collars wages.

Table 7: Robustness checks: contemporaneous shocks

	(1)	(2)	(3)	(4)
Dependent Variable:	Δ wage All	Δ share WC	Δ wage WC	Δ wage BC
1) Sector-year dummies: Import intensity (1995-2007)				
NIIov	0.092***	0.026**	0.033	0.099***
	[0.018]	[0.013]	[0.036]	[0.022]
Obs.	415,490	415,490	415,490	415,490
R2	0.030	0.005	0.008	0.028
First stage coefficient	0.946***	0.946***	0.946***	0.946***
	[0.077]	[0.077]	[0.077]	[0.077]
Kleibergen-Paap F-Statistic	151.69	151.69	151.69	151.69
2) Sector-year dummies: Export intensity (1995-2007)				
NIIov	0.117***	0.044***	0.044	0.122***
	[0.021]	[0.010]	[0.027]	[0.028]
Obs.	415,490	415,490	415,490	415,490
R2	0.030	0.005	0.008	0.028
First stage coefficient	0.942***	0.942***	0.942***	0.942***
	[0.060]	[0.060]	[0.060]	[0.060]
Kleibergen-Paap F-Statistic	248.7	248.7	248.7	248.7
3) Sector-year dummies: Output (1995-2007)				
NIIov	0.108***	0.017	0.058***	0.108***
	[0.024]	[0.013]	[0.022]	[0.029]
Obs.	415,490	415,490	415,490	415,490
R2	0.032	0.005	0.009	0.03
First stage coefficient	0.884***	0.884***	0.884***	0.884***
	[0.093]	[0.093]	[0.093]	[0.093]
Kleibergen-Paap F-Statistic	90.01	90.01	90.01	90.01
4) Sector-year dummies: Capital intensity (1995-2007)				
NIIov	0.071**	0.033***	0.045	0.073**
	[0.031]	[0.012]	[0.039]	[0.035]
Obs.	415,490	415,490	415,490	415,490
R2	0.030	0.005	0.008	0.028
First stage coefficient	0.947***	0.947***	0.947***	0.947***
	[0.051]	[0.051]	[0.051]	[0.051]
Kleibergen-Paap F-Statistic	339.83	339.83	339.83	339.83
5) Sector-year dummies: Material intensity (1995-2007)				
NIIov	0.117***	0.044***	0.036	0.123***
	[0.038]	[0.009]	[0.033]	[0.046]
Obs.	415,490	415,490	415,490	415,490
R2	0.030	0.005	0.008	0.028
First stage coefficient	0.905***	0.905***	0.905***	0.905***
	[0.086]	[0.086]	[0.086]	[0.086]
Kleibergen-Paap F-Statistic	111.55	111.55	111.55	111.55

Standard errors are corrected for clustering within industries.
***, **, * = indicate significance at the 1, 5 and 10% level, respectively.

Table 8: Robustness checks: underlying trends

	(1)	(2)	(3)	(4)
Dependent Variable:	Δ wage All	Δ share WC	Δ wage WC	Δ wage BC
1) Pre-sample change in import intensity (1990-1995)				
NIIov	0.121***	0.048***	0.040	0.125***
	[0.036]	[0.015]	[0.040]	[0.041]
Obs.	415,490	415,490	415,490	415,490
R2	0.029	0.004	0.008	0.027
First stage coefficient	0.844***	0.844***	0.844***	0.844***
	[0.071]	[0.071]	[0.071]	[0.071]
Kleibergen-Paap F-Statistic	139.74	139.74	139.74	139.74
2) Pre-sample change in export intensity (1990-1995)				
NIIov	0.138***	0.029***	0.075**	0.149***
	[0.032]	[0.010]	[0.031]	[0.038]
Obs.	415,490	415,490	415,490	415,490
R2	0.030	0.004	0.008	0.027
First stage coefficient	0.947***	0.947***	0.947***	0.947***
	[0.072]	[0.072]	[0.072]	[0.072]
Kleibergen-Paap F-Statistic	174.2	174.2	174.2	174.2
3) Pre-sample output growth (1990-1995)				
NIIov	0.126***	0.042***	0.050	0.127***
	[0.027]	[0.007]	[0.034]	[0.033]
Obs.	415,490	415,490	415,490	415,490
R2	0.029	0.004	0.008	0.027
First stage coefficient	0.915***	0.915***	0.915***	0.915***
	[0.093]	[0.093]	[0.093]	[0.093]
Kleibergen-Paap F-Statistic	97.58	97.58	97.58	97.58
4) Pre-sample change in capital intensity (1990-1995)				
NIIov	0.140***	0.041***	0.067**	0.144***
	[0.030]	[0.007]	[0.030]	[0.037]
Obs.	415,490	415,490	415,490	415,490
R2	0.030	0.004	0.008	0.027
First stage coefficient	0.922***	0.922***	0.922***	0.922***
	[0.089]	[0.089]	[0.089]	[0.089]
Kleibergen-Paap F-Statistic	106.83	106.83	106.83	106.83
5) Pre-sample change in material intensity (1990-1995)				
NIIov	0.135***	0.042***	0.062**	0.139***
	[0.027]	[0.009]	[0.030]	[0.034]
Obs.	415,490	415,490	415,490	415,490
R2	0.030	0.004	0.008	0.028
First stage coefficient	0.920***	0.920***	0.920***	0.920***
	[0.092]	[0.092]	[0.092]	[0.092]
Kleibergen-Paap F-Statistic	98.96	98.96	98.96	98.96

Standard errors are corrected for clustering within industries.
***, **, * = indicate significance at the 1, 5 and 10% level, respectively.

6 Worker-level evidence

The results identified so far are consistent with different, non-mutually exclusive micro-level adjustment dynamics. In particular, the increase in firm-level average wages for blue collars, in response to new imported inputs, could be driven both by higher earnings for continuing workers, i.e., the *intensive* margin, and by changes in the pool of employed workers, i.e., the *extensive* margin. In this section, we start exploiting the matched employer-employee nature of the INPS data to investigate the worker-level dynamics underlying our firm-level findings.

6.1 Continuing workers

We start by assessing the impact of new imported inputs on the wages of continuing workers, i.e., those workers that remain employed at the same firm over two years after the arrival of new imported inputs. The timing is thus fully consistent with the firm-level analysis.

We estimate the following specification:

$$\Delta Worker\_Wage_{izjt} = \alpha_{iz} + \alpha_t + \beta_1 NIIov_{jt-2} + \mathbf{I}_{it-2}\delta' + \mathbf{F}_{zt-2}\gamma' + \mathbf{S}_{jt-2}\lambda' + \varepsilon_{izjt}, \tag{4}$$

where i indexes individual workers, z firms, j industries, and t years.

$\Delta Worker\_Wage_{izjt}$ is the (log) wage growth of worker i between year t and $t-2$. The specification is estimated only on workers that remain employed at the same firm (z) over the two years. This allows us to investigate the impact of new imported inputs arriving in $t-2$ in industry j –i.e., $NIIov_{jt-2}$– on the wages of continuing workers within each firm.

α_t and α_{iz} are, respectively, year and worker-firm fixed effects. The inclusion of worker-firm fixed effects implies that we identify the effect of new imported inputs on the wages of individual workers only out of variations in their salary while they are employed within the same firm, even across more than one job-spell over time.

$\mathbf{F}_{zt-2}$ and $\mathbf{S}_{jt-2}$ are the same vectors of firm and industry-specific controls, measured at time $t-2$, as described in equation 3. $\mathbf{I}_{it-2}$ is instead a vector of worker-level controls in $t-2$. It includes: age; age squared; tenure within the firm; and tenure squared. In the regressions where white and blue-collar workers are pooled, we also include a dummy for white collars.

Overall, our identification strategy consists of comparing *changes* in individual wages across similar workers, who are continuously employed in similar firms operating in similar industries, except for the entry rate of new imported inputs.

Table 9 contains the results from the estimation of equation 4. The first three columns report OLS estimates of a basic specification, which includes year and worker-firm fixed effects, while excluding the three vectors of controls for worker, firm, and industry characteristics. Column 1 refers to the whole sample of continuing workers; column 2 is estimated only on white-collar workers; while column 3 contains estimates for the sample of blue-collar workers. In columns 3-6 we estimate the same specifications as in columns 1-3, but instrumenting $NIIov_{jt-2}$ using the arrival of new imported inputs in other European countries. Finally, in columns 7-9 we provide IV estimates of the complete specification outlined in equation 4, thus including also the three vectors of controls.

Table 9: Worker-level results: continuing workers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable:	Δ wage	Δ wage	Δ wage	Δ wage	Δ wage	Δ wage	Δ wage	Δ wage	Δ wage
Sample:	All	WC	BC	All	WC	BC	All	WC	BC
NIIov	0.039	0.027	0.035	0.045	0.044	0.031	0.012	0.032	-0.008
	[0.058]	[0.044]	[0.067]	[0.052]	[0.043]	[0.059]	[0.050]	[0.041]	[0.059]
Estimator	OLS	OLS	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Individual controls	no	no	no	no	no	no	yes	yes	yes
Firm controls	no	no	no	no	no	no	yes	yes	yes
Industry controls	no	no	no	no	no	no	yes	yes	yes
Employment spell effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Obs.	1,017,871	271,224	745,354	1,017,871	271,224	745,354	1,017,765	271,201	745,272
$R2$	0.015	0.01	0.018	0.015	0.01	0.018	0.019	0.014	0.021
First-stage results									
New Imported Inputs EU	-	-	-	0.909***	0.873***	0.922***	0.906***	0.883***	0.916***
	-	-	-	[0.092]	[0.093]	[0.090]	[0.092]	[0.088]	[0.093]
Kleibergen-Paap F-Statistic	-	-	-	98.47	87.82	104.12	97.05	101.51	97.4

Standard errors are corrected for clustering within industries. ***, **, * = indicate significance at the 1, 5 and 10% level, respectively.

Across the board, we never find any significant effects of new imported inputs on the wages of continuing workers. This suggests that the identified effects on firm-level wages are more likely to be driven by the *extensive* rather than the *intensive* margin. That is, by changes in the workforce at the firm level, rather than by changes in the wages of continuously employed workers. We investigate the effect of new imported inputs on worker mobility in the next sections.

6.2 Job separations

To investigate the impact of new imported inputs on job separations, we estimate regressions of the following form:

$$Prob(Separation_{izjt}) = \alpha_{iz} + \alpha_t + \beta_1 NIIov_{jt-2} + \mathbf{I}_{it-2}\delta^{'} + \mathbf{F}_{zt-2}\gamma^{'} + \mathbf{S}_{jt-2}\lambda^{'} + \varepsilon_{izjt}, \quad (5)$$

where i indexes individual workers, z firms, j industries, and t years.

$Separation_{izjt}$ is a dummy equal to 1 in case worker i, who is employed at firm z in year $t-2$, stops working for firm z over the next two years. The rest of the specification is exactly the same as in equation 4 for the analysis of continuing workers' wages. The main explanatory variable is always the arrival of new imported inputs in year $t-2$, and we keep controlling for time and worker-firm fixed effects, on top of including the three vectors of worker, firm, and industry controls at $t-2$.

Table 10 presents the baseline estimates of equation 5. The model is estimated separately for blue collars (left panel) and white collars (right panel). Moreover, within each category of workers, we further differentiate between low-wage and high-wage workers. Low-wage workers in each category are the ones whose salary is below the mean salary paid by the firm for their category, in year $t-2$. Conversely, high-wage workers are above the mean. In each of the two panels, the first two columns refer to OLS estimations, while the second two columns report IV estimates, where new imported inputs in Italy are instrumented using the arrival of new imported inputs in other EU countries.

The results suggest that new imported inputs increase significantly the probability of job separation for low-wage blue-collar workers, while their high-wage counterparts, as well as white-collar workers, do not seem to be affected. For high-wage blue collars, the coefficient on new imported inputs is actually negative and significant in the OLS regression of column 2, suggesting that new imported inputs might also reduce the odds of job separation among these workers. However, the coefficient is still negative but loses significance in the IV estimation of column 4. In terms of magnitudes, the coefficient of $NIIov$ in the IV regression of column 3 indicates that a one-standard-deviation increase in the arrival of new imported inputs (3.2 p.p.) leads to an increase in the probability of job separation for low-wage blue collars by around 1.2 percentage points. This corresponds to about 6% of their average probability of job separation (0.20).

In table 11, we assess the sensitivity of our findings to changing the definition of low-wage workers. In particular, in panel (1) the group of low-wage workers includes only those individuals earning less than the mean firm-level salary in each category, minus 5%. In panels (2) and (3), the threshold is lowered down to the mean salary minus 10% and 20%, respectively. Finally, in panel (4) we adopt as a threshold the median wage for each category of workers at the industry level. All regressions are two-stage least squares, and they confirm the baseline IV findings of Table 10. That is, the arrival of new imported inputs increases the probability of job separation for low-wage blue-collar workers only.

Table 10: Separations: low wage defined as below firm mean wage

Dependent Variable: Prob. Separation	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample:	**Blue collar workers**				**White collar workers**			
Sub-sample:	Low wage	High wage	Low wage	High wage	Low wage	High wage	Low wage	High wage
NIIov	0.292***	-0.209***	0.387***	-0.053	-0.120	-0.027	-0.072	0.010
	[0.054]	[0.042]	[0.062]	[0.093]	[0.079]	[0.085]	[0.141]	[0.185]
Estimator	OLS	OLS	2SLS	2SLS	OLS	OLS	2SLS	2SLS
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employment spell effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	370,432	494,627	370,432	494,627	192,904	154,343	176,971	138,659
R2	0.129	0.151	0.620	0.566	0.117	0.143	0.580	0.575
First-stage results								
New Imported Inputs EU	-	-	0.924***	0.902***	-	-	0.864***	0.885***
	-	-	[0.088]	[0.099]	-	-	[0.087]	[0.089]
Kleibergen-Paap F-Statistic	-	-	109.86	81.83	-	-	98.49	97.57

Standard errors are corrected for clustering within industries. ***, **, * = indicate significance at the 1, 5 and 10% level, respectively.

Table 11: Separations: robustness

Dependent Variable: Prob. Separation	(1)	(2)	(3)	(4)
Sample:	**Blue collar workers**		**White collar workers**	
Sub-sample:	Low wage	High wage	Low wage	High wage
1) Low wage: below firm mean wage minus 5%				
NIIov	0.349***	0.033	-0.155	0.055
	[0.069]	[0.081]	[0.120]	[0.192]
Obs.	241,085	625,992	149,518	166,836
R2	0.644	0.562	0.586	0.571
2) Low wage: below firm mean wage minus 10%				
NIIov	0.304**	0.063	-0.078	0.007
	[0.123]	[0.073]	[0.141]	[0.193]
Obs.	141,412	730,288	125,271	191,239
R2	0.668	0.562	0.594	0.568
3) Low wage: below firm mean wage minus 20%				
NIIov	0.664**	0.078	0.014	-0.011
	[0.253]	[0.068]	[0.210]	[0.178]
Obs.	38,766	848,445	75,811	241,657
R2	0.716	0.569	0.617	0.565
4) Low wage: below industry median wage				
NIIov	0.363***	0.010	-0.001	-0.040
	[0.071]	[0.100]	[0.112]	[0.249]
Obs.	421,780	455,333	157,756	160,290
R2	0.120	0.167	0.093	0.163

Standard errors are corrected for clustering within industries.
***, **, * = indicate significance at the 1, 5 and 10% level, respectively.

Summing up, our worker-level evidence is consistent with the firm-level findings. What seems to be emerging is the following pattern of adjustment: when new imported inputs arrive, firms are more likely to separate from low-wage blue-collar workers. At the same time, the job separation probability for white collars and high-wage blue collars is not affected. This entails a compositional shift in the workforce, with relatively more white-collar and high-wage blue-collar workers employed. At the firm level, the overall average wage increases. This seems to be purely driven by a compositional effect, i.e. by the growth of blue-collar average wages induced by job separations. In fact, the wages of continuing workers, both blue and white-collars, are not significantly affected.

7 Selection and assortative matching

To further characterize the adjustment process using matched employer-employee data, we apply the methodology developed by Abowd et al. (1999) (AKM henceforth), which has been applied in a large number of studies on the link between international trade and wages (e.g., Frías et al., 2009, Macis and Schivardi, 2016, and Helpman et al., 2017). The AKM methodology allows to decompose individual wages into several components, as related to time-variant worker characteristics, as well as time-invariant firm and worker fixed effects. The worker fixed effects are then interpreted as a proxy for individual features that are unobservable to the econometrician. The idea is that, conditional upon observable characteristics, higher individual wages reflect higher unobserved skills, which are captured by higher estimated worker fixed effects. A similar reasoning applies to firm fixed effects, for which higher values reflect better firm characteristics leading to higher wages, ceteris paribus.

Endowed with estimated firm and worker fixed effects from the AKM estimations, we perform two different analyses. First, we use the estimated worker fixed effects to investigate whether the arrival of new imported inputs leads to a positive selection of better workers at the industry level. Second, we test whether new imported inputs have any positive implications on the quality of matching between firms and workers, by which better workers are matched to better firms. In other words, we test whether new imported inputs lead to higher correlation between firm and worker fixed effects within industries, i.e., to positive assortative matching.

We implement the AKM methodology by estimating the following specification:

$$ln(Wage_{izjt}) = \alpha + \mathbf{X}_{it}\delta^{'} + \alpha_i + \alpha_z + \alpha_j + \alpha_t + \mathbf{Z}_{it}\gamma^{'} + \varepsilon_{izjt}, \tag{6}$$

where i indexes individual workers, z firms, j industries, and t years.

$\mathbf{X}_{it}$ is a set of individual time-variant worker characteristics. It includes: age, age squared, tenure within the firm, tenure squared, and a dummy for white collars. α_i and α_z are worker and firm fixed effects, respectively. α_j are 2-digit industry fixed effects, and α_t are year fixed effects. Finally, $\mathbf{Z}_{it}$ is a vector of interactions between all the explanatory variables and a dummy for females, as in Macis and Schivardi (2016).[15]

Importantly, equation 6 is estimated only on the group of connected observations, i.e., workers and firms that are connected by some events of job switching. Indeed, as discussed by Abowd et al. (2002), it is only within a connected group that worker and firm effects can be properly identified. The estimation group in our case contains 1,689,293 observations, which account for around 68% of the total sample of worker-level observations. The AKM methodology rests on the assumption of exogenous worker mobility, conditional on observables as well as on firm and worker fixed effects. Specifically, worker mobility should be independent of time-specific firm-level shocks, worker-firm match effects, and transitory wage shocks. In Appendix B we present a number of tests of this assumption, building on earlier work by Card et al. (2013), Card et al. (2015), and Macis and Schivardi (2016). Reassuringly, we find the mobility characteristics of our sample to be in line with the AKM assumption of exogenous mobility.

Table 12 reports estimation results for the first of the two analyses based on AKM estimates. The dependent variable is the average worker fixed effect, computed separately for each 2-digit industry and year. This is regressed over the baseline variable capturing the overall arrival of new imported inputs ($NIIov$) in year $t-2$, controlling for year fixed effects. The first three columns refer to OLS estimations, while columns 3 to 6 report

[15]The tenure data are censored because we do not have information on workers prior to 1995. To account for this censoring, we follow the same strategy employed by Macis and Schivardi (2016). In particular, for all the interested workers, we compute tenure as if they entered the firm in 1995, and we then interact this tenure variable with dummy variables indicating their age group in 1995. These interactions allow for different trajectories across different age groups. The groups are defined as follows: 16-24; 25-34; 35-44; 45-54; and 55-64.

IV estimates, where the baseline instrument is employed. Within each group of regressions, in the first column the average worker effect is evaluated over the pooled sample of blue and white-collar workers, while the second and third columns, respectively, refer separately to white and blue-collar workers.

We find evidence of a positive effect of new imported inputs on the average skills of workers employed in each industry. This finding seems to be driven by a positive selection effect on blue-collar workers, while there is no significant impact of new imported inputs on the average skills of white collars. These results are fully in line with our findings on wages and job separations. In particular, the arrival of new imported inputs seems to determine not only more job separations among low-wage blue-collar workers, but also an overall improvement in the average unobserved skills of employed blue-collar workers at the industry level. The magnitude of the effect is not negligible: the IV coefficient of column 6 implies that a one-standard-deviation increase in $NIIov$ (0.032) leads to an increase in the average unobserved skills of blue collars by about 0.06, which corresponds to around 30% of the standard deviation.

Finally, in Table 13 we assess the impact of new imported inputs on the quality of matching between firms and workers. The structure of the table is the same as in Table 12. The dependent variable is the correlation between firm and worker fixed effects, computed separately for each industry and year. The results suggest that the arrival of new imported inputs has a significant effect on the extent of positive assortative matching at the industry level. Also in this case, the effect seems to be driven by blue-collar workers, while there is no significant impact on white collars. In particular, according to the IV coefficient of column 6, a one-standard-deviation increase in $NIIov$ (0.032) leads to an improvement in assortative matching by about 0.08, which corresponds to around 56% of the standard deviation. By and large, this evidence is in line with the other findings, and points to a further important effect of new imported inputs in terms of improved allocative efficiency. Our findings are also complementary to recent results by Bombardini et al. (2015), who find a positive effect of exporting on worker-firm matching in France.

Table 12: Worker heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	**Mean Worker Fixed Effects**					
Sample:	All Workers	White Collar	Blue Collar	All Workers	White Collar	Blue Collar
NIIov	4.008***	0.187	4.178***	1.672*	-0.873	1.728*
	[0.765]	[0.870]	[0.791]	[0.950]	[0.685]	[0.985]
Estimator	OLS	OLS	OLS	2SLS	2SLS	2SLS
Year effects	yes	yes	yes	yes	yes	yes
Obs.	286	286	286	286	286	286
R2	0.508	0.412	0.519	0.448	0.395	0.459
First-stage results						
New Imported Inputs EU	-	-	-	0.815***	0.815***	0.815***
	-	-	-	[0.045]	[0.045]	[0.045]
Kleibergen-Paap F-Statistic	-	-	-	324.00	324.00	324.00

Standard errors are corrected for clustering within industries.
***, **, * = indicate significance at the 1, 5 and 10% level, respectively.

Table 13: Assortative matching

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	**Assortative Matching**					
Sample:	All Workers	White Collar	Blue Collar	All Workers	White Collar	Blue Collar
NIIov	3.844***	0.862	4.221***	2.299***	0.610	2.468***
	[0.603]	[1.527]	[0.633]	[0.740]	[1.210]	[0.854]
Estimator	OLS	OLS	OLS	2SLS	2SLS	2SLS
Year effects	yes	yes	yes	yes	yes	yes
Obs.	286	283	286	286	283	286
R2	0.329	0.064	0.320	0.280	0.064	0.268
First-stage results						
New Imported Inputs EU	-	-	-	0.815***	0.790***	0.815***
	-	-	-	[0.045]	[0.045]	[0.045]
Kleibergen-Paap F-Statistic	-	-	-	324.00	313.64	324.00

Standard errors are corrected for clustering within industries.
***, **, * = indicate significance at the 1, 5 and 10% level, respectively.

8 Discussion and possible channels

Our empirical evidence depicts a situation of industry transformation. The arrival of new imported inputs leads to a compositional change in the workforce, with a higher share of white-collar workers employed, and a selection of the higher wage, and higher skilled, blue-collar workers. The quality of matching between firms and workers also tends to improve in industries witnessing higher entry of new imported inputs.

The effects we identify are consistent with several findings of earlier literature on the impact of imported inputs. In particular, Colantone and Crinò (2014) show that new imported inputs lead to higher entry of new domestic products in the importing countries. This effect is driven by two channels, as domestic producers benefit from both wider and better sets of intermediate inputs, evaluated in terms of price-quality ratios. Moreover, Colantone and Crinò (2014) also find that the newly introduced domestic products tend to be upgraded as compared to previously produced goods. In particular, new products sell on average at a higher price, and are characterized by higher quality, as inferred from a market share premium conditional on prices (as in Khandelwal et al., 2013). To the extent that the introduction of new upgraded products requires relatively higher skills, product entry could be one channel driving our findings.

In Table 14 we provide some suggestive evidence along these lines. In particular, we replicate the baseline firm-level analysis as in columns 9-12 of Table 3 on two separate groups of industries, characterized by high vs. low entry rates of new domestic products. More specifically, an industry is classified in the first group if the cumulated entry rate of new domestic products, over the sample period, is above the median. Conversely, industries in the second group are below the median. The yearly entry rate of new domestic products in each industry is computed based on Eurostat-PRODCOM data as explained in Section 5.3, in line with Colantone and Crinò (2014).

The results in the left panel of Table 14 refer to firms operating in industries characterized by relatively high entry of new products. The findings are in line with the baseline evidence of Table 3. That is, new imported inputs lead to an increase in average wages at the firm level. This is driven by an increase in the share of white collars, and by higher growth in the average wage of blue-collar workers. Instead, for the less innovative industries, in the right panel, the coefficients of $NIIov$ are positive but not statistically different from zero. Overall, this evidence suggests that our general results on the effects of new imported inputs might be driven especially by firms active in industries witnessing more product entry over the sample. This is line with a positive role of new imported inputs in determining higher product innovation, which entails an upgrade of the workforce.

Earlier literature has also shown that imported inputs induce productivity gains and improvements in export performance, which might also go hand-in-hand with an upgrade of the workforce (Bas and Strauss-Kahn, 2014, and Bas and Strauss-Kahn, 2015). In line with this, in Table 15 we perform an analysis similar to the one in Table 14, but splitting industries according to their average export intensity over the sample period:

above the median in the left panel; below the median in the right panel. Also in this case, we obtain suggestive evidence that the general effects of new imported inputs are driven in particular by firms operating in industries that are more active in terms of exports.

To conclude, our evidence seems to suggest that new imported inputs matter especially in the most dynamic industries, which innovate and export relatively more, adjusting their workforce consistently.

Table 14: Heterogeneity: new products

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High Entry of New Products				**Low Entry of New Products**			
Dependent Variable:	Δ wage All	Δ share WC	Δ wage WC	Δ wage BC	Δ wage All	Δ share WC	Δ wage WC	Δ wage BC
NIIov	0.143***	0.044***	0.028	0.149***	0.104	0.045	0.084	0.105
	[0.046]	[0.009]	[0.032]	[0.055]	[0.105]	[0.031]	[0.096]	[0.127]
Estimator	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Firm controls	yes	yes	yes	yes	yes	yes	yes	yes
Industry controls	yes	yes	yes	yes	yes	yes	yes	yes
Firm effects	yes	yes	yes	yes	yes	yes	yes	yes
Year effects	yes	yes	yes	yes	yes	yes	yes	yes
Obs.	208,085	208,085	208,085	208,085	207,405	207,405	207,405	207,405
R2	0.03	0.005	0.009	0.027	0.029	0.004	0.008	0.027
Kleibergen-Paap F-Statistic	422.1	422.1	422.1	422.1	33.51	33.51	33.51	33.51

Standard errors are corrected for clustering within industries.
***, **, * = indicate significance at the 1, 5 and 10% level, respectively.

Table 15: Heterogeneity: export intensity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High Export Intensity				**Low Export Intensity**			
Dependent Variable:	Δ wage All	Δ share WC	Δ wage WC	Δ wage BC	Δ wage All	Δ share WC	Δ wage WC	Δ wage BC
NIIov	0.142***	0.042***	0.051	0.140***	0.072	0.032	0.072	0.105
	[0.033]	[0.007]	[0.043]	[0.038]	[0.078]	[0.023]	[0.045]	[0.095]
Estimator	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Firm controls	yes	yes	yes	yes	yes	yes	yes	yes
Industry controls	yes	yes	yes	yes	yes	yes	yes	yes
Firm effects	yes	yes	yes	yes	yes	yes	yes	yes
Year effects	yes	yes	yes	yes	yes	yes	yes	yes
Obs.	196,035	196,035	196,035	196,035	219,455	219,455	219,455	219,455
R2	0.028	0.004	0.008	0.026	0.033	0.005	0.008	0.03
Kleibergen-Paap F-Statistic	102.8	102.8	102.8	102.8	219.7	219.7	219.7	219.7

Standard errors are corrected for clustering within industries.
***, **, * = indicate significance at the 1, 5 and 10% level, respectively.

9 Conclusion

We have studied the effects of new imported inputs on wages and worker mobility, using a matched employer-employee dataset on the Italian manufacturing sector, between 1995 and 2007. This dataset has been linked to industry-level data on the arrival of new imported inputs, identified at the disaggregated 8-digit product level. Our results show that new imported inputs have a positive effect on average wage growth at the firm level. This positive effect is driven by two factors: (1) an increase in the white-collar/blue-collar ratio; and (2) an increase in wage growth for blue-collar workers. When performing the analysis at the individual level, we find that the increase in blue-collar wages is determined by the displacement of the lowest paid workers. Instead, we find no significant effects of new imported inputs on the wages of continuously employed individuals, irrespectively of their category.

We have employed the methodology by Abowd et al. (1999) to estimate worker and firm fixed effects in wage regressions. Endowed with these estimates, we have found that new imported inputs have a positive effect on the average unobserved skills of employed workers, as inferred from higher worker fixed effects. Moreover, we have provided evidence that new imported inputs have a positive impact on the correlation between firm and worker fixed effects, that is, on the extent of positive assortative matching at the industry level. Consistent with the findings on job separations, these effects on worker selection and allocative efficiency seem to be mostly driven by blue-collar workers.

Overall, our results depict a situation of industry transformation as a result of global sourcing opportunities. The evidence we provide is in line with earlier studies in the literature, which have shown how imported inputs have a positive effect on product innovation and export performance (Colantone and Crinò, 2014, Bas and Strauss-Kahn, 2014, and Bas and Strauss-Kahn, 2015). In particular, we provide suggestive evidence that our general results are mostly driven by firms operating in the most dynamic industries, characterized by more product innovation and better export performance: two features that are consistent with the upgrade of the workforce uncovered by our findings.

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Appendix

A Data

Table A1: Data Availability

	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

B AKM: tests of the exogenous mobility assumption

The estimation methodology by Abowd et al. (1999) rests on the assumption of exogenous worker mobility, conditional on observables as well as on firm and worker fixed effects. In this section, we provide supportive evidence for this hypothesis, following earlier work by Card et al. (2013), Card et al. (2015), and Macis and Schivardi (2016).

One possible concern is that worker mobility might be correlated with worker-firm match specific effects. That is, workers would move away from firms where the match effect is small, to join firms where the match effect is larger. To address this issue, we need to investigate whether there is a sorting of workers based on their match fixed

Table A2: Low-income countries

Afghanistan	Ethiopia	Moldova
Albania	Gambia	Mozambique
Angola	Georgia	Nepal
Armenia	Ghana	Niger
Azerbaijan	Guinea	Pakistan
Bangladesh	Guinea Bissau	Rwanda
Benin	Guyana	Samoa
Bhutan	Haiti	Sao Tome
Burkina Faso	India	Sierra Leone
Burundi	Kenya	Somalia
Cambodia	Lao PDR	Sri Lanka
Central African Rep.	Lesotho	St. Vincent
Chad	Madagascar	Sudan
China	Malawi	Togo
Comoros	Maldives	Uganda
Congo	Mali	Vietnam
Equatorial Guinea	Mauritania	Yemen
Eritrea		

effects. We accomplish this task by studying the wage changes of job movers. Under the assumption of exogenous mobility, workers moving from a high-firm-effect job to a low-firm-effect job should experience a wage loss, while workers moving in the opposite direction should experience a wage increase. Moreover, the wage loss of the first group of workers should be approximately symmetrical to the wage gain of the second group. Instead, workers moving across firms with similar fixed effects should not display significant wage changes.

In line with Macis and Schivardi (2016), in Table A3 we split firms into quartiles based on their fixed effects, and we assign switching workers to 16 different cells: one for each combination of origin-firm and destination-firm quartiles. We then compute the workers' average (log) wage in each cell for each year, and the overall wage change between 2 years before the job switch and 2 years after it. The evidence supports the exogenous mobility assumption: average wages increase for workers that move from a lower to a higher fixed-effect quartile –monotonically with respect to the gap in quartiles– while they decrease for switchers in the opposite direction. In particular, considering the movement from the first to the fourth quartile, the average wage increase is around 8%, very close in absolute terms to the wage loss for switchers in the opposite direction (-

Table A3: Wage dynamics

Origin/ Destination Quartile	N. Of obs.	Mean log Wage of Movers: 2 years before	1 year before	1 year after	2 years after	Changes from 2 years before to 2 years after
1 to 1	4927	5.84	5.86	5.88	5.90	0.01
1 to 2	1542	5.89	5.91	6.08	6.11	0.04
1 to 3	759	5.83	5.86	6.15	6.20	0.06
1 to 4	384	5.81	5.84	6.24	6.32	0.08
2 to 1	1288	5.97	5.98	5.88	5.87	-0.02
2 to 2	3939	6.08	6.06	6.11	6.12	0.01
2 to 3	2374	6.12	6.14	6.21	6.24	0.02
2 to 4	700	6.04	6.09	6.30	6.36	0.05
3 to 1	496	6.02	6.05	5.82	5.80	-0.04
3 to 2	1370	6.04	6.06	6.03	6.03	0.00
3 to 3	3778	6.17	6.18	6.22	6.23	0.01
3 to 4	1844	6.18	6.20	6.30	6.35	0.03
4 to 1	260	6.17	6.22	5.81	5.75	-0.07
4 to 2	486	6.13	6.17	5.96	5.94	-0.03
4 to 3	1161	6.13	6.16	6.09	6.09	-0.01
4 to 4	5174	6.23	6.25	6.29	6.30	0.01

7%). Instead, wage changes for workers that move from one firm to another within the same quartile are negligible. These patterns are also visualized in Figures 1 and 2. By and large, the mobility of workers does not seem to be systematically driven by worker-firm match effects.

Figure 1: Movers from the 1st and 4th quartiles

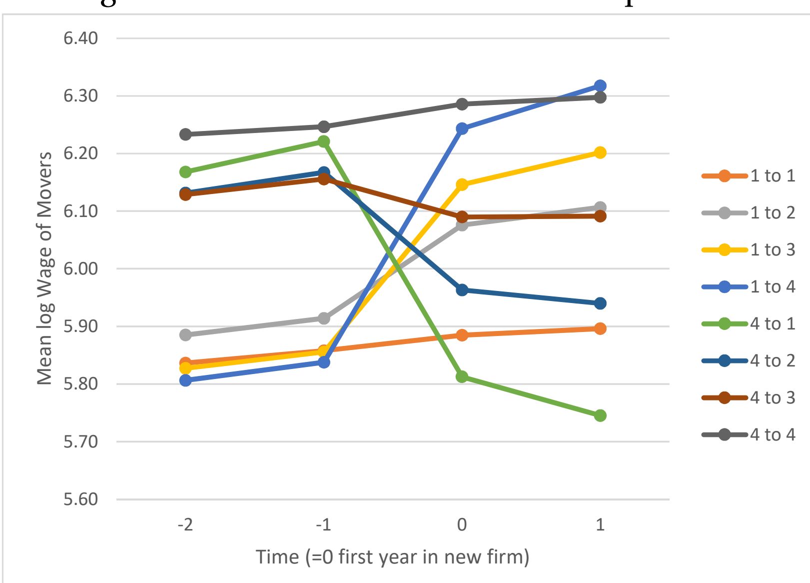
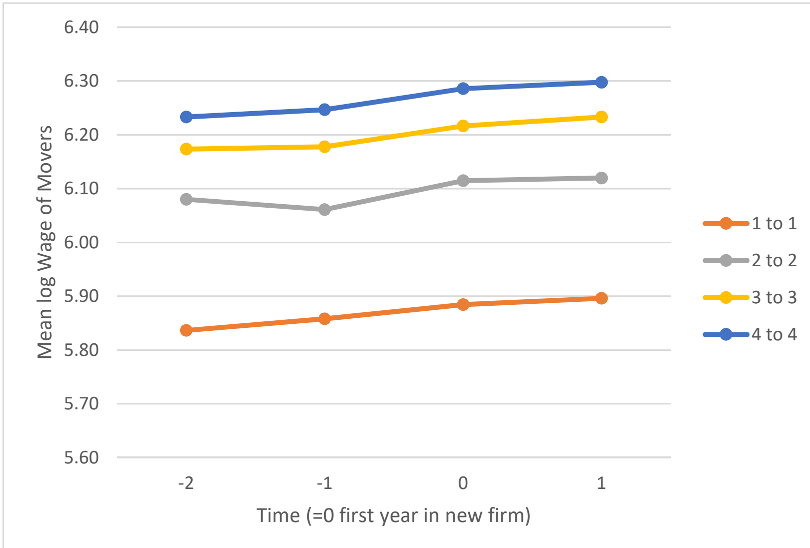


Figure 2: Movers within the same quartile



To provide additional corroborating evidence on this point, we have augmented the baseline AKM econometric specification by including worker-firm match effects. If such effects were relevant, we should have observed a sizable improvement in statistical fit. As a matter of fact, though, we only observed very small changes. Specifically, the adjusted R-squared grew from 0.87 to 0.88, while the Root MSE grew from 0.14 to 0.15. These results further reassure us on the validity of the exogenous mobility assumption with respect to worker-firm match effects.

A second possible concern is that worker mobility is correlated with time-specific firm-wide shocks. That is, workers would move away from firms that are experiencing bad shocks to join firms that are experiencing good shocks. Card et al. (2015) argue that, if that is the case, then we should observe a wage drop for workers just before they change firms. Reassuringly, Figure 1 shows no evidence of such a pattern. If anything, workers experience on average negligible wage increases before switching: between t-2 and t-1.

A third source of violation for the exogenous mobility assumption is related to transitory wage shocks. Specifically, workers who displayed good performance would be more likely to move to high-wage firms, while under-performing workers would move to low-wage firms. Again, Figure 1 does not show any evidence of such a pattern, as negligible increases in wages before the move are observed in all cases, regardless of the specific transition that takes place.

Finally, in Figure 3 we show the average residuals from the AKM estimations across 100 cells, formed by the combination of the deciles of firm and worker fixed effects. This is meant to check for the existence of any systematic patterns in the distribution of residuals across worker-firm matches. Residuals tend to be very small (lower than 0.005), with some larger values appearing only for the lowest-deciles of worker and firm fixed effects.

Overall, the evidence presented in this section is in line with earlier results by Card et al. (2013), Card et al. (2015), and Macis and Schivardi (2016), and points to the validity of the exogenous mobility assumption. Hence, the results of Section 7 appear to be based on reliable estimates of the unobserved worker and firm components of wages.

Figure 3: Distribution of residuals