

Colantone, Italo; Matano, Alessia; Naticchioni, Paolo

Working Paper

New Imported Inputs, Wages and Worker Mobility

IZA Discussion Papers, No. 12715

Provided in Cooperation with:

IZA – Institute of Labor Economics

Suggested Citation: Colantone, Italo; Matano, Alessia; Naticchioni, Paolo (2019) : New Imported Inputs, Wages and Worker Mobility, IZA Discussion Papers, No. 12715, Institute of Labor Economics (IZA), Bonn

This Version is available at:

<https://hdl.handle.net/10419/207539>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

DISCUSSION PAPER SERIES

IZA DP No. 12715

**New Imported Inputs, Wages and Worker
Mobility**

Italo Colantone
Alessia Matano
Paolo Naticchioni

OCTOBER 2019

DISCUSSION PAPER SERIES

IZA DP No. 12715

New Imported Inputs, Wages and Worker Mobility

Italo Colantone

Bocconi University

Alessia Matano

University of Barcelona

Paolo Naticchioni

Roma Tre University, IZA and INPS

OCTOBER 2019

Any opinions expressed in this paper are those of the author(s) and not those of IZA. Research published in this series may include views on policy, but IZA takes no institutional policy positions. The IZA research network is committed to the IZA Guiding Principles of Research Integrity.

The IZA Institute of Labor Economics is an independent economic research institute that conducts research in labor economics and offers evidence-based policy advice on labor market issues. Supported by the Deutsche Post Foundation, IZA runs the world's largest network of economists, whose research aims to provide answers to the global labor market challenges of our time. Our key objective is to build bridges between academic research, policymakers and society.

IZA Discussion Papers often represent preliminary work and are circulated to encourage discussion. Citation of such a paper should account for its provisional character. A revised version may be available directly from the author.

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

New Imported Inputs, Wages and Worker Mobility*

We study how firms and industries adjust to increasing international trade in intermediate inputs. In particular, 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 assortative 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 increase in the degree of positive assortative matching between firms and workers.

JEL Classification: J01, J31, F14

Keywords: new imported inputs, wages, matched employer-employee data

Corresponding author:

Paolo Naticchioni
Roma Tre University
Via Chiabrera 199
00145 Rome
Italy

E-mail: p.naticchioni@gmail.com12

* We thank Alessandro Borin, Rosario Crinò, Florian Mayneris, Luca Nunziata, seminar participants at the Catholic University of Louvain, Norwegian University of Science and Technology, University of Milan, University of Bergen, University of Padua, the CRIE Joint Research Center of Ispra, the AIEL Conference in Trento, and the SIE Conference in Milan for useful comments. Italo Colantone gratefully acknowledges financial support from the JPMorgan Foundation, within the project "New Skills at Work". Alessia Matano gratefully acknowledges financial support from Spain's Ministerio de Ciencia e Innovación, through action ECO2016-75805-R. The usual disclaimer applies.

1 Introduction

The most recent globalization wave has been characterized by a rapid expansion of global value chains, especially between the mid-1990s and the financial crisis of 2007-2008. This phenomenon has transformed the organization of industries on a global scale, with a pervasive break-up of production processes across multiple countries (Johnson and Noguera, 2017; Timmer et al., 2014). This has entailed an upsurge of international trade in intermediate inputs (Feenstra, 1998; Feenstra and Hanson, 1999; Yi, 2003), with a sizable increase in the number of *new* imported intermediates worldwide (Broda and Weinstein, 2006; Goldberg et al., 2009; Colantone and Crinò, 2014).

What are the effects of trade in intermediates on firm and industry dynamics? 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). Surprisingly, little attention has been paid to the effects of imported inputs on wages and worker mobility. The only available studies have focused on the impact of input tariff reductions and import flows on wages and skill premia in Indonesia, Turkey, and China (Amiti and Davis, 2011, Amiti and Cameron, 2012, Meschi et al., 2011, Chen et al., 2017), obtaining mixed results.

In this paper we focus on Italy, an advanced industrialized economy, and we employ a direct measure of the arrival of new imported inputs to provide the first comprehensive assessment of their effects on wage dynamics, on the skill-composition of the labor force, on worker mobility, and on assortative matching between firms and workers. Overall, our aim is to shed light on the broader picture of industry transformation driven by global sourcing opportunities in a developed country.

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 increase in the degree of positive assortative matching between firms and workers.

Overall, our findings describe a process of industry transformation driven by trade in intermediates. 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 an impact on worker-firm matching, with an increase in the extent to which higher-skilled workers are matched to better firms.

Our evidence is in line with earlier theoretical and empirical results pointing to different channels through which imported inputs might determine higher wage growth through an upgrade of the workforce. In particular, Colantone and Crinò (2014) show that new imported inputs lead to higher entry of new domestic products, which tend

to be upgraded as compared to previously produced goods, as they sell on average at a higher price, and are characterized by higher quality. Moreover, Bas and Strauss-Kahn (2014, 2015) provide evidence of a positive effect of imported inputs on both quantity and quality of exports. To the extent that such upgrades in domestic activities require relatively higher skills, these industry dynamics could be important channels behind our findings. For instance, using US data, Xiang (2005) finds that newly introduced goods shift labor demand in favor of skilled labor. Moreover, there is evidence that imported tools and machines are complementary to higher skills, and thus tend to propagate skill-biased technical change across countries (Burstein et al., 2013, Koren et al., 2019).

We provide suggestive evidence that the effects of new imported inputs that we identify tend to be more prevalent in industries characterized by higher product innovation rates and higher export intensity over the sample. Moreover, we also show that new imported imports have distinctive implications as compared to more general measures of offshoring. Our findings complement recent evidence on the positive effects of low-wage import competition on skill upgrading in Italy (Consoli et al., 2016), and on firm selection across countries in Western Europe (Colantone et al., 2014).

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). 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. This approach is standard in the empirical trade literature (see, e.g., Broda and Weinstein, 2006; Goldberg et al., 2009; Goldberg et al., 2010, and follows closely Colantone and Crinò (2014), who show how domestic producers might benefit from new imported inputs by having access to both *wider* and *better* sets of intermediates, as defined in

terms of improved price-quality ratios. In line with that, a new imported variety might reflect both the very first time in which a given input is imported in Italy from abroad, and the addition of an extra country of origin for an input that was already imported from somewhere, which can improve the set of available intermediates through more favorable price-quality characteristics. In the empirical analysis, we show that our results are robust to using a narrower definition of new imported inputs, which considers only the very first time in which a given input is imported from abroad. Our procedure for identifying new imported inputs 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 product range of 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 minimum 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., 2019), 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, with the related endogeneity concerns and the instrumental variable employed in the econometric analysis, and we present the matched employer-employee data. In Section 4 we describe the firm-level results, while the worker-level evidence is presented in Section 5. Section 6 contains results on worker selection and assortative matching. Section 7 provides a comprehensive discussion of the results, along with suggestive evidence on some possible channels. Section 8 concludes.

2 Related literature

This paper is related to different strands of empirical studies which have investigated the implications of international trade for firm and industry dynamics. Broadly speaking, trade liberalization can be conceptualized as a fundamental driver of Schumpeterian industrial transformation. In a globalizing environment, firms are exposed to more competition from foreign producers, but they can also exploit new opportunities in terms of larger export markets for their final products, and expanded options for input sourcing.

Adapting firm strategies to exploit these opportunities is key for firm survival, innovation, and growth (Coucke et al., 2007, Coucke and Sleuwaegen, 2008, Fassio, 2017).

More specifically, 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 1990s. 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. Similar evidence is found by Meschi et al. (2011) for Turkey. In contrast with these studies, Amiti and Cameron (2012) find evidence of a negative effect of lower input tariffs on skill premia at importing firms in Indonesia.

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 assortative matching between firms and workers.

3 Data and methodology

3.1 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 com-

pute 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). 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 assess 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. Changes of the second type are problematic for our purposes, as they reflect renaming of products rather than the entry of new products in the set of imports.

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

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 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, or 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 domestic producers in terms of efficiency and 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

²The 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.

country.

To illustrate our empirical approach and provide some intuition on the role of new imported inputs, it might be useful to provide some illustrative examples for Italy over the sample period. Between 1996 and 2002, Italy starts importing “parts and accessories for machines and appliances for testing the mechanical properties of materials” (CN 90249000) from several countries, including Hungary, Romania, Slovenia, Croatia, and Morocco. The same product code used to be imported from higher wage countries such as France, Germany and the US in previous years. The new imported varieties might then lead to efficiency gains for domestic companies through improved price-quality ratios, which in turn might result in improved export performance and more product innovation. As a matter of fact, the Eurostat PRODCOM database on domestic production reports the introduction of new “electronic machines and appliances for testing the mechanical properties of metals” (PC 33206210) in Italy in the year 2004. To provide an example of the very first imported variety of an input, in 1999 Italy imports for the first time “machine-tools for dry-etching patterns on LCD substrates” (CN 84569950). The country of origin is the US. In 2001, the Eurostat PRODCOM database reports the introduction of new “optical devices, appliances and instruments” (PC 33402359) in Italy. From both examples, one can grasp how new imported inputs, in either way, might have an impact on wages and on the composition of the workforce through a change in domestic activities.

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

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

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 is an *horizontal* indicator for input entry, in the sense that it considers only inputs belonging to the product range of a given industry. Yet, as a matter of fact, firms within each industry source their intermediates also from other industries, which creates *vertical* linkages. For instance, firms in the textile industry purchase both textile inputs, such as knitted fabrics, and machinery inputs, such as components of sewing machines. Hence, to capture more comprehensively the arrival of new imported inputs within the country that are relevant for the firms belonging to each industry, we follow Colantone and Crinò (2014) and compute the following indicator:

$$NIIov_{jt} = \sum_k \phi_{jk} \cdot NII_{kt}. \quad (2)$$

$NIIov_{jt}$ 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 minimum 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.³ Yet, it is important to stress how new imported inputs are always

³To provide information on the variability of $NIIov$ between and within broad industries, we aggregate our 22 2-digit industries in 14 sub-sections, corresponding to the next level of aggregation in the NACE Rev 1.1. classification. Sub-sections are denoted by two-character alphabetical codes (from DA to

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.

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 against the lagged overall arrival of new imported inputs in the corresponding industry: $NIIov_j$. A concern with our analysis is the possible endogeneity of new imported inputs. Endogeneity might stem both from reverse causality (e.g., higher wage growth in Italy pushing firms to source more inputs from abroad, leading to an upward bias in OLS), and from omitted variables (e.g., unobserved negative supply shocks in Italy inducing both lower wage growth and more new imported inputs, with a downward bias in OLS).

These concerns are mitigated by the fact that our specifications always include year dummies, as well as a rich set of fixed effects and time-varying controls (see *infra*). In addition, we run instrumental variable regressions. We instrument the overall arrival of

DN for the manufacturing sector). We compute the average $NIIov$ of each 2-digit industry across all years. This mean variable has an average of about 11%, with a standard deviation of 1.4%. When we regress the average $NIIov$ of each 2-digit industry on the 14 dummies for each sub-section, we obtain an R-squared of 0.58, thus pointing to a substantial degree of residual variability within each broader industry.

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., 2019).

3.2 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.⁴

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 a 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

⁴In 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.

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.⁵ 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%).⁶

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 54.86.⁷ The average share of white collars out of total workers is equal to 26%, 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%).

⁵In all our analyses, 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.

⁶As in Macis and Schivardi (2016), we have dropped records in the first and last percentiles of the wage distributions.

⁷The total number of employees has a minimum of zero. This refers to single entrepreneurs working at firms with no additional employees.

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

Notes. Source: INPS matched employer-employee database.

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

Notes. Source: INPS matched employer-employee database.

4 Firm-level evidence

4.1 Econometric specification

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

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

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; 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. We use the second lag of $NIIov$ in the baseline specification to allow enough time for the effects of new imported inputs to materialize after their arrival. Nevertheless, in Section 4.2 we discuss the robustness of our findings to using alternative lags, from one to five.

\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.

4.2 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 estimations 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.

Table 3: Firm-level results: baseline

Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	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
NIlov	0.131*** [0.036]	0.033*** [0.009]	0.048 [0.039]	0.134*** [0.042]	0.136*** [0.034]	0.039*** [0.009]	0.083 [0.054]	0.135*** [0.040]	0.126*** [0.032]	0.042*** [0.007]	0.052 [0.032]	0.129*** [0.039]
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	0.251	0.255	0.230	0.236	0.251	0.255	0.230	0.236	0.251	0.258	0.230	0.236
First-stage results												
New Imported Inputs EU	-	-	-	-	0.926*** [0.088]	0.926*** [0.088]	0.926*** [0.088]	0.926*** [0.088]	0.921*** [0.089]	0.921*** [0.089]	0.921*** [0.089]	0.921*** [0.089]
Kleibergen-Paap F-Statistic	-	-	-	-	110.8	110.8	110.8	110.8	107.0	107.0	107.0	107.0

Notes. The dependent variables are indicated in columns' headings. *NIlov* is the overall indicator for the arrival of new imported inputs at the industry level, as defined in eq. 2. *Firm controls* include the second lag of firm age and firm size, measured as the total number of employees (in logs). *Industry controls* include the second lag of labor productivity, capital intensity, material intensity, export intensity, and import intensity. Columns (1)-(4) report OLS estimates. Columns (5)-(12) report 2SLS estimates. The instrument, *New Imported Inputs EU*, is the arrival rate of new imported inputs in other EU countries. The standard errors are corrected for clustering within industries. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

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 2.1%, 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.

In Figure 1 of Appendix C we show that the estimated effects of new imported inputs are statistically significant and very similar to the baseline estimates if we employ the third or fourth lag of *NIIov*, while they become statistically insignificant if we use the fifth lag. When employing the first lag of *NIIov*, we obtain similar findings to our baseline specification, although the effects on wages are smaller and imprecisely estimated. This is in line with the idea that it might take more than one year for the effects of new imported inputs to fully materialize at the firm level.⁸

4.3 Robustness and sensitivity

In Tables 4 and 5, we submit our baseline results to several 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

⁸In the regressions employing alternative lags of *NIIov*, we always change the rest of the specification accordingly. For example, when using the fourth lag of *NIIov*, we compute wage growth between year t and $t - 4$, and we include firm- and industry-level controls measured in year $t - 4$.

lag of NII_j , 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 NII_{ov} , 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, NII_{ov} , 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.⁹ 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 NII_{ov} 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 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

⁹See Colantone and Crinò (2014) for a complete explanation of the identification of new domestic products.

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 NII_{ov} 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 NII_{ov} focusing only on imported input varieties from the set of 52 low-income countries identified by Bernard et al. (2006).¹⁰ 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, suggesting that new imported inputs might generate similar effects on wages regardless of their different sources. The magnitudes of the estimated effects are very similar across panels if one takes into account the differences in standard deviations

¹⁰These 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.

among the three versions of $NIIov$. In particular, $NIIov$ from low-income countries has a standard deviation of 0.29%. The coefficient in column 1 of panel (7) therefore implies that a one-standard-deviation increase in $NIIov$ from low-income countries leads to higher wage growth by around 0.4%, which is the same figure as obtained from the baseline estimation of column 9 in Table 3. The same effect is estimated in panel (8) for other countries, where $NIIov$ has a standard deviation of 3%. For OECD countries, in panel (9), the standard deviation of $NIIov$ is 2.15%, and the estimated effect on wage growth is around 0.5%. 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 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.¹¹ 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.

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 some weak evidence of a positive effect of new imported inputs on the average wage of white collars.

In Appendix B, we report a large number of additional robustness checks on the identification. 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 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, 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 partic-

¹¹The estimated coefficients in panel (4) are an order of magnitude larger than the baseline estimates of Table 3. However, if one takes into account the differences in standard deviations, the estimated effects are pretty close. For instance, according to the estimated coefficient of column 1 in panel (4), a one-standard-deviation increase in $NIIov$, equal to 0.28%, leads to higher wage growth by around 0.32%, close to the 0.4% baseline effect.

ular, 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. For example, we show that our findings remain unchanged when we re-construct the instrumental variable by focusing exclusively on the arrival of new imported inputs in the UK, a country whose business cycle is actually more correlated with the US than with continental Europe (Artis et al., 2004).

In addition to changing the instrument, we also probe the robustness of our results to the inclusion of 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, we include in the regressions *sector*-year dummies, where sectors are defined as groups of 2-digit industries witnessing similar dynamics in terms of various observable outcomes, such as import and export intensity, output growth, and material and capital intensity. In all cases, our evidence is essentially unaffected.

5 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.

5.1 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:

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

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 6 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 4-6 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.¹²

¹²Notice that the number of observations in the pooled estimations is greater than the sum of observations in the category-specific estimations. This is due to the fact that some workers switch category of employment over time within the same firm. The wage growth of these switchers is always considered in the pooled estimations, but some singletons are dropped in the category-specific estimations, due to the inclusion of worker-firm fixed effects. In unreported regressions, we have checked that the overall results of columns 1, 4, and 7 do not meaningfully change when pooling the samples of, respectively, columns 2-3, 5-6, and 8-9. That is, dropping the singleton switchers also from the pooled estimations.

Table 4: Robustness checks: additional variables

Dependent Variable:	(1)	(2)	(3)	(4)
	Δ wage All	Δ share WC	Δ wage WC	Δ wage BC
1) Only new imported inputs within the same industry				
NIIj	0.083*** [0.020]	0.021*** [0.007]	0.041 [0.028]	0.079*** [0.025]
Obs.	415,371	415,371	415,371	415,371
R2	0.251	0.258	0.230	0.236
2) Including new domestic inputs				
NIlov	0.124*** [0.031]	0.038*** [0.010]	0.051 [0.034]	0.129*** [0.039]
Share of new domestic inputs	0.075 [0.085]	0.006 [0.014]	-0.017 [0.056]	0.071 [0.096]
Obs.	376,666	376,666	376,666	376,666
R2	0.261	0.268	0.239	0.246
3) Including new imported final goods				
NIlov	0.139*** [0.031]	0.042*** [0.007]	0.056 [0.036]	0.147*** [0.039]
Share of new imported final goods	-0.088** [0.039]	-0.002 [0.010]	-0.032 [0.031]	-0.117*** [0.044]
Obs.	415,490	415,490	415,490	415,490
R2	0.252	0.258	0.230	0.237
4) Including overall value of imported inputs				
NIlov	0.101*** [0.031]	0.039*** [0.007]	0.034 [0.033]	0.105*** [0.039]
ln(value of all imported inputs)	-0.020** [0.008]	-0.002 [0.002]	-0.014** [0.006]	-0.019** [0.010]
Obs.	415,371	415,371	415,371	415,371
R2	0.252	0.258	0.230	0.237
5) Controlling for share of inputs out of total imports				
NIlov	0.084** [0.036]	0.032*** [0.009]	0.025 [0.039]	0.086* [0.046]
Share of inputs over total imports: same industry	-0.062 [0.044]	-0.015 [0.011]	-0.039 [0.030]	-0.065 [0.047]
Obs.	415,490	415,490	415,490	415,490
R2	0.252	0.258	0.230	0.237
6) Controlling for share of inputs out of total imports				
NIlov	0.084** [0.034]	0.033*** [0.008]	0.028 [0.038]	0.090** [0.044]
Share of inputs over total imports: overall	-0.132** [0.063]	-0.028 [0.018]	-0.073** [0.037]	-0.122 [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				
NIlov from low-income countries	1.532*** [0.264]	0.301** [0.121]	0.461 [0.284]	1.538*** [0.308]
Obs.	415,490	415,490	415,490	415,490
R2	0.251	0.258	0.230	0.236
8) Focus on inputs from all other countries				
NIlov from all other countries	0.140*** [0.039]	0.048*** [0.008]	0.064 [0.041]	0.143*** [0.047]
Obs.	415,490	415,490	415,490	415,490
R2	0.251	0.258	0.230	0.236
9) Focus on inputs from OECD countries				
NIlov from OECD countries	0.256*** [0.095]	0.085*** [0.022]	0.129 [0.080]	0.263** [0.109]
Obs.	415,490	415,490	415,490	415,490
R2	0.251	0.258	0.230	0.236

Notes. The dependent variables are indicated in columns' headings. The specifications are the same as in columns (9)-(12) of Table 3 except for the changes specified in each panel. All estimations are 2SLS. The standard errors are corrected for clustering within industries. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table 5: Robustness checks: alternative measure

	(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*** [0.035]	0.045*** [0.008]	0.058* [0.036]	0.140*** [0.042]
Obs.	415,490	415,490	415,490	415,490
R2	0.251	0.258	0.230	0.236
2) Weights from Use Matrices (year-specific)				
NIIov	0.155*** [0.036]	0.044*** [0.007]	0.060 [0.038]	0.163*** [0.046]
Obs.	415,490	415,490	415,490	415,490
R2	0.251	0.258	0.230	0.237
3) Weights from Use Matrices (average)				
NIIov	0.154*** [0.035]	0.042*** [0.009]	0.070 [0.044]	0.159*** [0.046]
Obs.	415,490	415,490	415,490	415,490
R2	0.251	0.258	0.230	0.237
4) Only new inputs imported for all years after entry				
NIIov	1.148*** [0.317]	0.281*** [0.059]	0.520*** [0.184]	1.173*** [0.373]
Obs.	415,490	415,490	415,490	415,490
R2	0.251	0.258	0.230	0.236
5) Net entry				
NIIov	0.058*** [0.022]	0.015*** [0.006]	0.022 [0.016]	0.067*** [0.023]
Obs.	415,490	415,490	415,490	415,490
R2	0.251	0.258	0.230	0.237
6) Only first varieties				
Net entry of imported inputs	0.086*** [0.021]	0.030*** [0.005]	0.023 [0.017]	0.091*** [0.027]
Obs.	415,490	415,490	415,490	415,490
R2	0.251	0.258	0.230	0.236
7) Excluding capital goods				
NIIov	0.108*** [0.030]	0.042*** [0.006]	0.053* [0.028]	0.101*** [0.039]
Obs.	415,490	415,490	415,490	415,490
R2	0.251	0.258	0.230	0.236
8) Excluding capital goods, fuels, and lubricants				
NIIov	0.101*** [0.031]	0.041*** [0.006]	0.047* [0.025]	0.092** [0.040]
Obs.	415,490	415,490	415,490	415,490
R2	0.251	0.258	0.230	0.236

Notes. The dependent variables are indicated in columns' headings. The specifications are the same as in columns (9)-(12) of Table 3 except for the changes specified in each panel. All estimations are 2SLS. The standard errors are corrected for clustering within industries. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table 6: Worker-level results: continuing workers

Dependent Variable: Sample:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Δ wage All	Δ wage WC	Δ wage BC	Δ wage All	Δ wage WC	Δ wage BC	Δ wage All	Δ wage WC	Δ wage BC
NIlov	0.039 [0.058]	0.027 [0.044]	0.035 [0.067]	0.045 [0.053]	0.044 [0.044]	0.031 [0.060]	0.012 [0.052]	0.032 [0.042]	-0.008 [0.061]
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
Worker-firm 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	0.256	0.281	0.240	0.256	0.281	0.240	0.258	0.284	0.243
First-stage results									
New Imported Inputs EU	-	-	-	0.909*** [0.092]	0.873*** [0.093]	0.922*** [0.090]	0.906*** [0.092]	0.883*** [0.088]	0.916*** [0.093]
Kleibergen-Paap F-Statistic	-	-	-	98.47	87.82	104.12	97.05	101.51	97.4

Notes. The dependent variables and the estimation samples are indicated in columns' headings. *NIlov* is the overall indicator for the arrival of new imported inputs at the industry level, as defined in eq. 2. *Individual controls* include the second lag of 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. *Firm controls* include the second lag of firm age and firm size, measured as the total number of employees (in logs). *Industry controls* include the second lag of labor productivity, capital intensity, material intensity, export intensity, and import intensity. Columns (1)-(3) report OLS estimates. Columns (4)-(9) report 2SLS estimates. The instrument, *New Imported Inputs EU*, is the arrival rate of new imported inputs in other EU countries. The 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.¹³ We investigate the effect of new imported inputs on worker mobility in the next sections.

5.2 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 7 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

¹³In Table A6 of Appendix C we replicate all the baseline firm-level results of Table 3, restricting the sample to firm-year observations for which there is at least one continuing worker considered in Table 6. The results are virtually unchanged compared to the baseline firm-level estimates. This suggests that the differences between firm-level and worker-level results documented so far are not driven by sample selection.

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. 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 8, 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 7. That is, the arrival of new imported inputs increases the probability of job separation for low-wage blue-collar workers only.¹⁴

¹⁴In Table A7 of Appendix C, we show that similar findings on job separations are obtained when estimating pooled regressions for all blue-collar and white-collar workers, where we interact the arrival of new imported inputs with a category-specific dummy for low-wage workers.

Table 7: Separations: low wage defined as below firm mean wage

Dependent Variable: Job Separation	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)			
	Low wage	Higher wage	Low wage	Higher wage	Low wage	Higher wage	Low wage	Higher wage	Low wage	Higher wage	Low wage	Higher wage	Low wage	Higher wage	Low wage	Higher wage		
Sample:	Blue collar workers																	
Sub-sample:	White collar workers																	
NIlov	0.292*** [0.063]	-0.209 [0.149]	0.387*** [0.062]	-0.053 [0.093]	-0.120 [0.110]	-0.027 [0.159]	-0.072 [0.141]	0.010 [0.185]										
Estimator	OLS	OLS	2SLS	2SLS	OLS	OLS	2SLS	2SLS	OLS	OLS	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Industry controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Worker-firm effects	Yes	Yes	Yes	Yes	Yes	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	Yes	Yes	Yes	Yes	Yes	
Obs.	370,432	494,627	370,432	494,627	176,971	138,659	176,971	138,659	176,971	176,971	138,659	176,971	138,659	176,971	176,971	138,659	138,659	
R2	0.620	0.566	0.620	0.566	0.580	0.575	0.580	0.566	0.580	0.580	0.575	0.580	0.575	0.580	0.580	0.575	0.575	
First-stage results																		
New Imported Inputs EU	-	-	0.925*** [0.088]	0.902*** [0.099]	-	-	0.864*** [0.087]	0.885*** [0.089]	-	-	-	-	-	-	-	-	-	-
Kleibergen-Paap F-Statistic	-	-	109.86	81.83	-	-	98.49	97.57	-	-	-	-	-	-	-	-	-	

Notes: The dependent variable is a dummy for job separation. The estimation samples are indicated in columns' headings. All estimations are 2SLS. *NIlov* is the overall indicator for the arrival of new imported inputs at the industry level, as defined in eq. 2. *Individual controls* include the second lag of 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. *Firm controls* include the second lag of firm age and firm size, measured as the total number of employees (in logs). *Industry controls* include the second lag of labor productivity, capital intensity, material intensity, export intensity, and import intensity. Columns (1)-(2) and (5)-(6) report OLS estimates. Columns (3)-(4) and (7)-(8) report 2SLS estimates. The instrument, *New Imported Inputs EU*, is the arrival rate of new imported inputs in other EU countries. The standard errors are corrected for clustering within industries. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table 8: Separations: robustness

Dependent Variable: Job Separation	(1)	(2)	(3)	(4)
Sample:	Blue collar workers		White collar workers	
Sub-sample:	Low wage	Higher wage	Low wage	Higher wage
1) Low wage: below firm mean wage minus 5%				
NIIov	0.349*** [0.069]	0.033 [0.081]	-0.155 [0.120]	0.055 [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** [0.123]	0.063 [0.073]	-0.078 [0.141]	0.007 [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** [0.253]	0.078 [0.068]	0.014 [0.210]	-0.011 [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*** [0.072]	0.010 [0.103]	-0.001 [0.115]	-0.040 [0.255]
Obs.	421,780	455,333	157,756	160,290
R2	0.620	0.559	0.597	0.566

Notes. The dependent variable is a dummy for job separation. The estimation samples are indicated in columns' headings and detailed in each panel. All estimations are 2SLS. The specifications are the same as in columns (3)-(4) and (7)-(8) of Table 7. The 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.

6 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 investigate whether new imported inputs have any impact on the extent of positive assortative matching between firms and workers. In other words, we test whether new imported inputs lead to higher correlation between firm and worker fixed effects within industries.

We implement the AKM methodology by estimating the following specification:

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

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 D 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 9 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 IV estimates, where the baseline instrument is employed. Within each group of regres-

¹⁵The 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.

Table 9: 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
<i>NIIov</i>	4.008*** [0.765]	0.187 [0.870]	4.178*** [0.791]	1.672* [0.950]	-0.873 [0.685]	1.728* [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*** [0.045]	0.815*** [0.045]	0.815*** [0.045]
Kleibergen-Paap F-Statistic	-	-	-	324.00	324.00	324.00

Notes. The dependent variable is the average worker fixed effect at the industry level. This is computed over the sample of workers indicated in columns' headings. Columns (1)-(3) report OLS estimates. Columns (4)-(6) report 2SLS estimates. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

sions, 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 10 we assess the impact of new imported inputs on assortative match-

Table 10: 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
<i>NIIov</i>	3.844*** [0.603]	0.862 [1.527]	4.221*** [0.633]	2.299*** [0.740]	0.610 [1.210]	2.468*** [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*** [0.045]	0.790*** [0.045]	0.815*** [0.045]
Kleibergen-Paap F-Statistic	-	-	-	324.00	313.64	324.00

Notes. The dependent variable is the correlation between firm and worker fixed effects at the industry level. This is computed over the sample of workers indicated in columns' headings. Columns (1)-(3) report OLS estimates. Columns (4)-(6) report 2SLS estimates. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

ing between firms and workers. The structure of the table is the same as in Table 9. 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 increase 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 significant effect of new imported inputs on the allocation of workers to firms. Our findings are also complementary to recent results by Bombardini et al. (2015), who document similar effects of exporting on worker-firm matching in France.

7 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 degree of positive assortative matching between firms and workers also tends to increase 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. Moreover, the newly introduced domestic products tend to be upgraded as compared to previously produced goods. They 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, as suggested by Xiang (2005), product entry could be one channel driving our findings.

In Table 11 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 4.3.

The results in the left panel of Table 11 refer to firms operating in industries charac-

Table 11: 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
<i>NIIov</i>	0.143** [0.051]	0.044*** [0.010]	0.028 [0.035]	0.149* [0.060]	0.104 [0.109]	0.045 [0.032]	0.084 [0.099]	0.105 [0.131]
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	0.250	0.252	0.228	0.236	0.254	0.264	0.232	0.237
Kleibergen-Paap F-Statistic	422.1	422.1	422.1	422.1	33.51	33.51	33.51	33.51

Notes. The dependent variables are indicated in columns' headings. The specifications are the same as in columns (9)-(12) of Table 3. All estimations are 2SLS. The first four columns refer to firms operating in industries where the cumulated entry rate of new domestic products, over the sample period, is above the median. The remaining columns refer to industries below the median. The standard errors are corrected for clustering within industries. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

terized 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 findings on the effects of new imported inputs tend to be more prevalent in industries witnessing more product entry over the sample. The selection of industries into the two groups is endogenous to the arrival of new imported inputs, so the differences in results could be driven both by selection effects and by the fact that the basic effects of imported inputs are stronger in more innovative industries. In either way, these results provide descriptive evidence in line with the idea that new imported inputs might be connected to higher product innovation and a related upgrade of the workforce.

Table 12: 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
NIlov	0.142*** [0.035]	0.042*** [0.007]	0.051 [0.045]	0.140*** [0.039]	0.072 [0.083]	0.032 [0.025]	0.072 [0.048]	0.105 [0.102]
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	0.254	0.269	0.234	0.238	0.251	0.248	0.228	0.237
Kleibergen-Paap F-Statistic	102.8	102.8	102.8	102.8	219.7	219.7	219.7	219.7

Notes. The dependent variables are indicated in columns' headings. The specifications are the same as in columns (9)-(12) of Table 3. All estimations are 2SLS. The first four columns refer to firms operating in industries whose average export intensity over the sample period is above the median. The remaining columns refer to industries below the median. The standard errors are corrected for clustering within industries. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

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, 2015). In line with this, in Table 12 we perform an analysis similar to the one in Table 11, 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, and with the same caveat as above, 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 suggests that the effects of new imported inputs are more evident in the most dynamic industries, where firms innovate and export relatively more, adjusting their workforce consistently.

8 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 assortative matching 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 the effects of new imported inputs in our context tend to be more prevalent 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.

References

- Abowd, J. M., Creecy, R. H., and Kramarz, F. (2002). Computing person and firm effects using linked longitudinal employer-employee data. *Center for Economic Studies, US Census Bureau*, 2002-06.
- Abowd, J. M., Kramarz, F., and Margolis, D. N. (1999). High wage workers and high wage firms. *Econometrica*, 67(2):251–333.
- Amiti, M. and Cameron, L. (2012). Trade liberalization and the wage skill premium: Evidence from indonesia. *Journal of International Economics*, 87(2):277–287.
- Amiti, M. and Davis, D. R. (2011). Trade, firms, and wages: theory and evidence. *Review of Economic Studies*, 79(1):1–36.
- Amiti, M. and Konings, J. (2007). Trade liberalization, intermediate inputs, and productivity: evidence from Indonesia. *American Economic Review*, 97(5):1611–1638.
- Artis, M., Marcellino, M., and Proietti, T. (2004). Dating business cycles: a methodological contribution with an application to the Euro area. *Oxford Bulletin of Economics and Statistics*, 66(4):537–565.
- Autor, D., Dorn, D., and Hanson, G. H. (2013). The China syndrome: local labor market effects of import competition in the United States. *American Economic Review*, 103(6):2121–68.
- Bas, M. and Strauss-Kahn, V. (2014). Does importing more inputs raise exports? Firm-level evidence from France. *Review of World Economics*, 150(2):241–275.
- Bas, M. and Strauss-Kahn, V. (2015). Input-trade liberalization, export prices and quality upgrading. *Journal of International Economics*, 95(2):250–262.
- Bernard, A. B., Jensen, J. B., and Schott, P. K. (2006). Survival of the best fit: exposure to low-wage countries and the (uneven) growth of US manufacturing plants. *Journal of International Economics*, 68(1):219–237.
- Bloom, N., Draca, M., and Van Reenen, J. (2016). Trade induced technical change? The impact of chinese imports on innovation, IT and productivity. *Review of Economic Studies*, 83(1):87–117.
- Bombardini, M., Orefice, G., and Tito, M. D. (2015). Does exporting improve matching? Evidence from French employer-employee data. *NBER Working Paper*, 21225.
- Broda, C. and Weinstein, D. E. (2006). Globalization and the gains from variety. *Quarterly Journal of Economics*, 121(2):541–585.
- Burstein, A., Cravino, J., and Vogel, J. (2013). Importing skill-biased technology. *American Economic Journal: Macroeconomics*, 5(2):32–71.

- Card, D., Cardoso, A. R., and Kline, P. (2015). Bargaining, sorting, and the gender wage gap: quantifying the impact of firms on the relative pay of women. *Quarterly Journal of Economics*, 131(2):633–686.
- Card, D., Heining, J., and Kline, P. (2013). Workplace heterogeneity and the rise of West German wage inequality. *Quarterly Journal of Economics*, 128(3):967–1015.
- Chen, B., Yu, M., and Yu, Z. (2017). Measured skill premia and input trade liberalization: evidence from Chinese firms. *Journal of International Economics*, 109:31–42.
- Colantone, I., Coucke, K., and Sleuwaegen, L. (2014). Low-cost import competition and firm exit: evidence from the eu. *Industrial and Corporate Change*, 24(1):131–161.
- Colantone, I. and Crinò, R. (2014). New imported inputs, new domestic products. *Journal of International Economics*, 92(1):147–165.
- Colantone, I., Crinò, R., and Ogliari, L. (2019). Globalization and mental distress. *Journal of International Economics*, forthcoming.
- Consoli, D., Vona, F., and Rentocchini, F. (2016). That was then, this is now: skills and routinization in the 2000s. *Industrial and Corporate Change*, 25(5):847–866.
- Coucke, K., Pennings, E., and Sleuwaegen, L. (2007). Employee layoff under different modes of restructuring: exit, downsizing or relocation. *Industrial and Corporate Change*, 16(2):161–182.
- Coucke, K. and Sleuwaegen, L. (2008). Offshoring as a survival strategy: evidence from manufacturing firms in belgium. *Journal of International Business Studies*, 39(8):1261–1277.
- Dauth, W., Findeisen, S., and Suedekum, J. (2014). The rise of the East and the Far East: German labor markets and trade integration. *Journal of the European Economic Association*, 12(6):1643–1675.
- Fassio, C. (2017). Export-led innovation: the role of export destinations. *Industrial and Corporate Change*, 27(1):149–171.
- Feenstra, R. C. (1998). Integration of trade and disintegration of production in the global economy. *Journal of Economic Perspectives*, 12(4):31–50.
- Feenstra, R. C. and Hanson, G. H. (1999). The impact of outsourcing and high-technology capital on wages: estimates for the United States, 1979–1990. *Quarterly Journal of Economics*, 114(3):907–940.
- Frías, J. A., Kaplan, D. S., and Verhoogen, E. A. (2009). Exports and wage premia: evidence from Mexican employer-employee data. *Columbia University mimeo*.

- Goldberg, P., Khandelwal, A., Pavcnik, N., and Topalova, P. (2009). Trade liberalization and new imported inputs. *American Economic Review Papers and Proceedings*, 99(2):494–500.
- Goldberg, P. K., Khandelwal, A. K., Pavcnik, N., and Topalova, P. (2010). Imported intermediate inputs and domestic product growth: evidence from India. *Quarterly Journal of Economics*, 125(4):1727–1767.
- Halpern, L., Koren, M., and Szeidl, A. (2015). Imported inputs and productivity. *American Economic Review*, 105(12):3660–3703.
- Helpman, E., Itzhoki, O., Muendler, M.-A., and Redding, S. J. (2017). Trade and inequality: from theory to estimation. *Review of Economic Studies*, 84(1):357–405.
- Hummels, D., Jørgensen, R., Munch, J., and Xiang, C. (2014). The wage effects of offshoring: evidence from Danish matched worker-firm data. *American Economic Review*, 104(6):1597–1629.
- Johnson, R. C. and Noguera, G. (2017). A portrait of trade in value-added over four decades. *Review of Economics and Statistics*, 99(5):896–911.
- Khandelwal, A. K., Schott, P. K., and Wei, S.-J. (2013). Trade liberalization and embedded institutional reform: evidence from Chinese exporters. *American Economic Review*, 103(6):2169–2195.
- Koren, M., Csillag, M., and Kálló, J. (2019). Machines and machinists: Importing skill-biased technology. *Central European University mimeo*.
- Macis, M. and Schivardi, F. (2016). Exports and wages: rent sharing, workforce composition, or returns to skills? *Journal of Labor Economics*, 34(4):945–978.
- Meschi, E., Taymaz, E., and Vivarelli, M. (2011). Trade, technology and skills: evidence from turkish microdata. *Labour Economics*, 18:S60–S70.
- Timmer, M. P., Dietzenbacher, E., Los, B., Stehrer, R., and de Vries, G. J. (2015). An illustrated user guide to the World Input-Output Database: the case of global automotive production. *Review of International Economics*, 23(3):575–605.
- Timmer, M. P., Erumban, A. A., Los, B., Stehrer, R., and de Vries, G. J. (2014). Slicing up global value chains. *Journal of Economic Perspectives*, 28(2):99–118.
- Topalova, P. and Khandelwal, A. (2011). Trade liberalization and firm productivity: the case of India. *Review of Economics and Statistics*, 93(3):995–1009.
- Xiang, C. (2005). New goods and the relative demand for skilled labor. *Review of Economics and Statistics*, 87(2):285–298.

Yi, K.-M. (2003). Can vertical specialization explain the growth of world trade? *Journal of Political Economy*, 111(1):52–102.

Yu, M. (2015). Processing trade, tariff reductions and firm productivity: evidence from Chinese firms. *Economic Journal*, 125(585):943–988.

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

Notes. Source: Eurostat.

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		

B Robustness checks on identification

In Table A3 we perform a number of robustness checks related to the instrumental variable. 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 (3) we compute the instrument by considering only 10 countries of Central and Eastern Europe that entered the EU between 2004 and 2007.¹⁶ Over our period of analysis, 1995-2007, these countries witnessed a process of transition and convergence towards the rest

¹⁶These countries are: Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Romania, Poland, Slovakia, Slovenia.

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 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.¹⁷ 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).¹⁸ Finally, in panel (6) we exclude the most energy intensive industries, as identified by the US Department of Energy.¹⁹ 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 A4 we augment the baseline specifications with different sets of fixed effects capturing time trends. 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

¹⁷These 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).

¹⁸These 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).

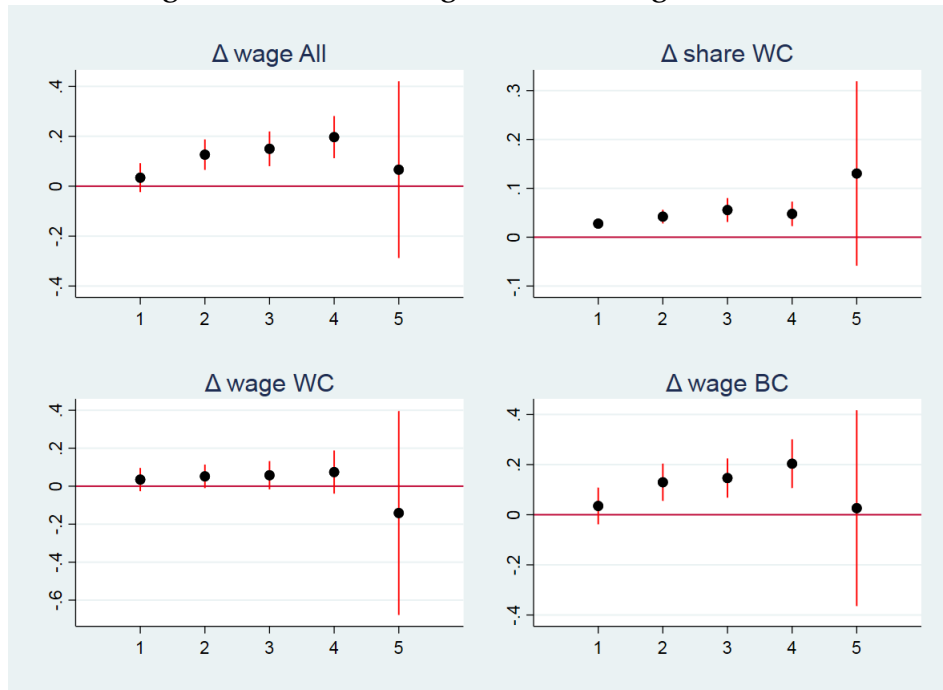
¹⁹These industries are: “pulp and paper” (NACE 21); “coke, petroleum products, and nuclear fuel” (NACE 23); “chemicals” (NACE 24); “non-metallic mineral products” (NACE 26); and “basic metals” (NACE 27).

outcomes. For instance, in panel (1) we focus on the growth in import intensity between 1995 and 2007. We measure 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 A5 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.

C Additional Results

Figure 1: Results using alternative lags of NII_{ov}



Notes. The dependent variables are indicated in each panel. The specifications are the same as in columns (9)-(12) of Table 3 except for the differences in lags. All estimations are 2SLS. The standard errors are corrected for clustering within industries.

Table A3: 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				
NIlov	0.122*** [0.033]	0.043*** [0.007]	0.051 [0.034]	0.125*** [0.040]
Obs.	415,490	415,490	415,490	415,490
R2	0.251	0.258	0.230	0.236
First stage coefficient	0.908*** [0.102]	0.908*** [0.102]	0.908*** [0.102]	0.908*** [0.102]
Kleibergen-Paap F-Statistic	78.92	78.92	78.92	78.92
2) Focusing on UK only				
NIlov	0.144*** [0.034]	0.037*** [0.010]	0.028 [0.025]	0.154*** [0.037]
Obs.	415,490	415,490	415,490	415,490
R2	0.251	0.258	0.230	0.236
First stage coefficient	0.827*** [0.043]	0.827*** [0.043]	0.827*** [0.043]	0.827*** [0.043]
Kleibergen-Paap F-Statistic	365.5	365.5	365.5	365.5
3) Focusing on 10 Central Eastern EU new Members				
NIlov	0.148** [0.070]	0.016 [0.022]	0.098 [0.079]	0.195** [0.084]
Obs.	225,918	225,918	225,918	225,918
R2	0.323	0.347	0.310	0.306
First stage coefficient	0.781*** [0.268]	0.781*** [0.268]	0.781*** [0.268]	0.781*** [0.268]
Kleibergen-Paap F-Statistic	8.48	8.48	8.48	8.48
4) Excluding most cyclical industries				
NIlov	0.144*** [0.032]	0.048*** [0.006]	0.050* [0.028]	0.153*** [0.040]
Obs.	354,811	354,811	354,811	354,811
R2	0.252	0.257	0.230	0.238
First stage coefficient	0.958*** [0.076]	0.958*** [0.076]	0.958*** [0.076]	0.958*** [0.076]
Kleibergen-Paap F-Statistic	158.67	158.67	158.67	158.67
5) Excluding most volatile industries (Autor et al., 2013)				
NIlov	0.166** [0.072]	0.018 [0.022]	0.142** [0.062]	0.200** [0.088]
Obs.	315,309	315,309	315,309	315,309
R2	0.252	0.254	0.230	0.237
First stage coefficient	0.845*** [0.056]	0.845*** [0.056]	0.845*** [0.056]	0.845*** [0.056]
Kleibergen-Paap F-Statistic	223.54	223.54	223.54	223.54
6) Excluding most energy-intensive industries				
NIlov	0.143*** [0.034]	0.048*** [0.007]	0.054* [0.029]	0.148*** [0.041]
Obs.	353,453	353,453	353,453	353,453
R2	0.253	0.261	0.232	0.239
First stage coefficient	0.934*** [0.091]	0.934*** [0.091]	0.934*** [0.091]	0.934*** [0.091]
Kleibergen-Paap F-Statistic	106.07	106.07	106.07	106.07

Notes. The dependent variables are indicated in columns' headings. The specifications are the same as in columns (9)-(12) of Table 3 except for the changes specified in each panel. All estimations are 2SLS. The standard errors are corrected for clustering within industries. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table A4: 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*** [0.018]	0.026** [0.013]	0.033 [0.036]	0.099*** [0.022]
Obs.	415,490	415,490	415,490	415,490
R2	0.252	0.258	0.231	0.238
First stage coefficient	0.946*** [0.077]	0.946*** [0.077]	0.946*** [0.077]	0.946*** [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*** [0.021]	0.044*** [0.011]	0.044 [0.028]	0.122*** [0.029]
Obs.	415,490	415,490	415,490	415,490
R2	0.252	0.258	0.231	0.238
First stage coefficient	0.942*** [0.060]	0.942*** [0.060]	0.942*** [0.060]	0.942*** [0.060]
Kleibergen-Paap F-Statistic	248.7	248.7	248.7	248.7
3) Sector-year dummies: Output (1995-2007)				
NIIov	0.108*** [0.025]	0.017 [0.014]	0.058*** [0.022]	0.108*** [0.030]
Obs.	415,490	415,490	415,490	415,490
R2	0.254	0.258	0.231	0.239
First stage coefficient	0.884*** [0.093]	0.884*** [0.093]	0.884*** [0.093]	0.884*** [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** [0.032]	0.033*** [0.012]	0.045 [0.040]	0.073** [0.036]
Obs.	415,490	415,490	415,490	415,490
R2	0.252	0.258	0.231	0.237
First stage coefficient	0.947*** [0.051]	0.947*** [0.051]	0.947*** [0.051]	0.947*** [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*** [0.039]	0.044*** [0.010]	0.036 [0.034]	0.123*** [0.047]
Obs.	415,490	415,490	415,490	415,490
R2	0.252	0.258	0.231	0.238
First stage coefficient	0.905*** [0.086]	0.905*** [0.086]	0.905*** [0.086]	0.905*** [0.086]
Kleibergen-Paap F-Statistic	111.55	111.55	111.55	111.55

Notes. The dependent variables are indicated in columns' headings. The specifications are the same as in columns (9)-(12) of Table 3 except for the inclusion of sector-year dummies, as described in each panel. All estimations are 2SLS. The standard errors are corrected for clustering within industries. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table A5: 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*** [0.036]	0.048*** [0.015]	0.040 [0.041]	0.125*** [0.042]
Obs.	415,490	415,490	415,490	415,490
R2	0.252	0.258	0.230	0.237
First stage coefficient	0.844*** [0.071]	0.844*** [0.071]	0.844*** [0.071]	0.844*** [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*** [0.033]	0.029*** [0.010]	0.075** [0.032]	0.149*** [0.039]
Obs.	415,490	415,490	415,490	415,490
R2	0.252	0.258	0.230	0.237
First stage coefficient	0.947*** [0.072]	0.947*** [0.072]	0.947*** [0.072]	0.947*** [0.072]
Kleibergen-Paap F-Statistic	174.2	174.2	174.2	174.2
3) Pre-sample output growth (1990-1995)				
NIIov	0.126*** [0.028]	0.042*** [0.007]	0.050 [0.035]	0.127*** [0.034]
Obs.	415,490	415,490	415,490	415,490
R2	0.252	0.258	0.230	0.237
First stage coefficient	0.915*** [0.093]	0.915*** [0.093]	0.915*** [0.093]	0.915*** [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*** [0.031]	0.041*** [0.007]	0.067** [0.031]	0.144*** [0.038]
Obs.	415,490	415,490	415,490	415,490
R2	0.252	0.258	0.230	0.237
First stage coefficient	0.922*** [0.089]	0.922*** [0.089]	0.922*** [0.089]	0.922*** [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*** [0.028]	0.042*** [0.009]	0.062* [0.031]	0.139*** [0.035]
Obs.	415,490	415,490	415,490	415,490
R2	0.252	0.258	0.231	0.238
First stage coefficient	0.920*** [0.092]	0.920*** [0.092]	0.920*** [0.092]	0.920*** [0.092]
Kleibergen-Paap F-Statistic	98.96	98.96	98.96	98.96

Notes. The dependent variables are indicated in columns' headings. The specifications are the same as in columns (9)-(12) of Table 3 except for the inclusion of sector-year dummies, as described in each panel. All estimations are 2SLS. The standard errors are corrected for clustering within industries. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table A6: Firm-level results: only firm-year observations with at least one continuing worker

Dependent Variable:	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)		(9)		(10)		(11)		(12)				
	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	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		
NIlov	0.131*** [0.035]		0.031*** [0.010]	0.038 [0.036]	0.138*** [0.041]	0.134*** [0.033]	0.038*** [0.009]	0.071 [0.049]	0.137*** [0.039]	0.126*** [0.032]	0.042*** [0.007]	0.039 [0.028]	0.133*** [0.038]														
Estimator	OLS	OLS	OLS	OLS	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	
Firm controls	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	yes	yes	yes	yes	yes	yes	yes	yes	yes	
Industry controls	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	yes	yes	yes	yes	yes	yes	yes	yes	yes	
Firm effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	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	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	
Obs.	385,598	385,598	385,598	385,598	385,598	385,598	385,598	385,598	385,598	385,598	385,598	385,598	385,598	385,598	385,598	385,598	385,598	385,572	385,572	385,572	385,572	385,572	385,572	385,572	385,572	385,572	
R2	0.256	0.261	0.234	0.234	0.241	0.256	0.261	0.234	0.241	0.257	0.264	0.234	0.241	0.257	0.264	0.234	0.241	0.257	0.264	0.234	0.234	0.234	0.234	0.234	0.234	0.241	
First-stage results																											
New Imported Inputs EU	-	-	-	-	-	0.927*** [0.087]	0.927*** [0.087]	0.927*** [0.087]	0.927*** [0.087]	0.923*** [0.088]	0.923*** [0.088]	0.923*** [0.088]	0.923*** [0.088]	0.923*** [0.088]	0.923*** [0.088]	0.923*** [0.088]	0.923*** [0.088]	0.923*** [0.088]	0.923*** [0.088]	0.923*** [0.088]	0.923*** [0.088]	0.923*** [0.088]	0.923*** [0.088]	0.923*** [0.088]	0.923*** [0.088]	0.923*** [0.088]	
Kleibergen-Paap F-Statistic	-	-	-	-	-	112.9	112.9	112.9	112.9	112.9	112.9	112.9	112.9	112.9	112.9	112.9	112.9	112.9	112.9	112.9	112.9	112.9	112.9	112.9	112.9	112.9	

Notes. The dependent variables are indicated in columns' headings. The estimation sample includes only firm-year observations with at least one continuing worker considered in Table 6. *NIlov* is the overall indicator for the arrival of new imported inputs at the industry level, as defined in eq. 2. *Firm controls* include the second lag of firm age and firm size, measured as the total number of employees (in logs). *Industry controls* include the second lag of labor productivity, capital intensity, material intensity, export intensity, and import intensity. Columns (1)-(4) report OLS estimates. Columns (5)-(12) report 2SLS estimates. The instrument, *New Imported Inputs EU*, is the arrival rate of new imported inputs in other EU countries. The standard errors are corrected for clustering within industries. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table A7: Separations: pooled regressions

Dependent Variable: Job Separation	(1)	(2)
Sample:	Blue collar	White collar
1) Low wage: below firm mean wage		
NIlov	-0.053 [0.093]	0.010 [0.185]
NIlov * Low wage dummy	0.440*** [0.120]	-0.082 [0.105]
Obs.	865,059	315,630
R2	0.592	0.578
Kleibergen-Paap F-Statistic	40.92	49.25
2) Low wage: below firm mean wage minus 5%		
NIlov	0.033 [0.081]	0.055 [0.192]
NIlov * Low wage dummy	0.316** [0.118]	-0.210 [0.136]
Obs.	867,077	316,354
R2	0.590	0.578
Kleibergen-Paap F-Statistic	41.64	49.07
3) Low wage: below firm mean wage minus 10%		
NIlov	0.063 [0.073]	0.007 [0.193]
NIlov * Low wage dummy	0.241 [0.163]	-0.085 [0.154]
Obs.	871,700	316,510
R2	0.585	0.579
Kleibergen-Paap F-Statistic	42.67	48.12
4) Low wage: below firm mean wage minus 20%		
NIlov	0.078 [0.068]	-0.011 [0.178]
NIlov * Low wage dummy	0.586** [0.282]	0.025 [0.198]
Obs.	887,211	317,468
R2	0.580	0.578
Kleibergen-Paap F-Statistic	45.18	45.22
5) Low wage: below industry median wage		
NIlov	0.010 [0.103]	-0.040 [0.255]
NIlov * Low wage dummy	0.353** [0.136]	0.039 [0.231]
Obs.	877,113	318,046
R2	0.591	0.580
Kleibergen-Paap F-Statistic	45.83	47.63

Notes. The dependent variable is a dummy for job separation. The estimation samples are indicated in columns' headings. The low wage dummies are category-specific and are constructed as detailed in each panel. All estimations are 2SLS. The specifications include the same controls and fixed effects as in Table 7. The standard errors are corrected for clustering within industries. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

D 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, 2015), and Macis and Schivardi (2016).

Table A8: Wage dynamics

Origin/ Destination Quartile	N. Of obs.	Mean log Wage of Movers				Changes from 2 years before
		2 years before	1 year before	1 year after	2 years after	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

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 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 A8 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 (-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 2 and 3. By and large, the mobility of workers does not seem to be systematically driven by worker-firm match effects.

Figure 2: Movers from the 1st and 4th quartiles

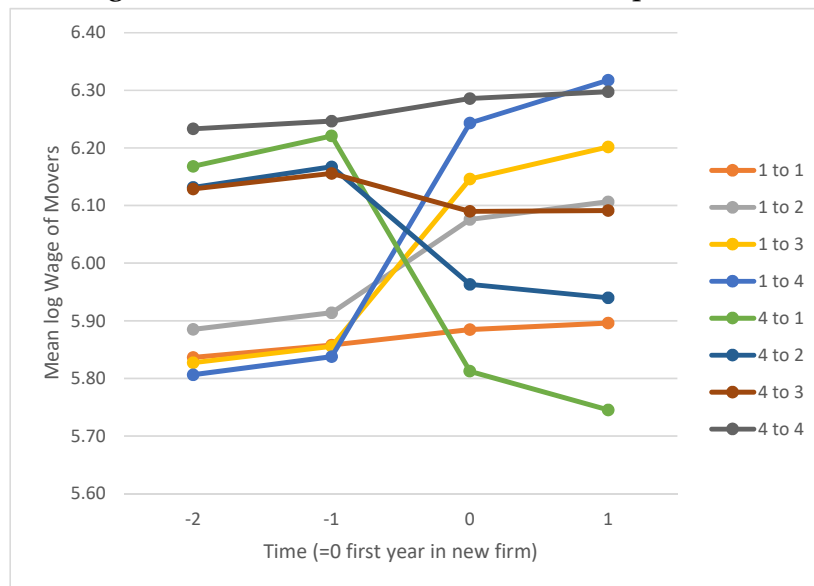
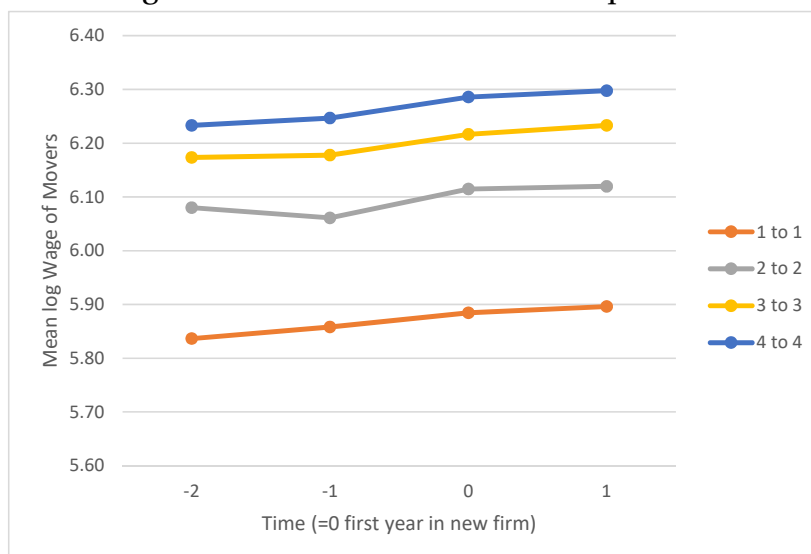


Figure 3: Movers within the same quartile



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 2 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 transi-

tory 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 2 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 4 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 6 appear to be based on reliable estimates of the unobserved worker and firm components of wages.

Figure 4: Distribution of residuals

