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Foreign direct investment and wage dispersion: Evidence from French employer-employee data[☆]

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ABSTRACT

This article investigates to what extent outward foreign direct investment (FDI) affects domestic wages. Results reveal that multinational companies pay a wage premium to their employees and the wage premium is increasing within the wage distribution. In a second step, we use a fixed effect and match effect model to analyze the effect of outward FDI within job spells. Results suggest that outward FDI raises manager wages by 0.077% and reduces wages for workers performing offshorable tasks by 0.34%. The positive effect of FDI on manager wages is mainly driven by the intensive margin of outward FDI. This result is observed even after controlling for endogenous worker mobility. Finally, we observe that the increase of outward foreign direct investment cause wages to be higher, and this effect is due to both multinational companies paying a wage premium and to changes in the market value of unobservable worker skills.

1. Introduction

One important issue in international economics is to understand to what extent globalization contributes to wage inequalities between- and within-demographic groups. A number of contributions have emerged in order to identify such sources of wage inequality.¹ Among this literature, scientific contributions on the specific role of outward foreign direct investment (FDI) on wage

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¹ The studies on import of intermediate inputs show that offshoring has increased wage inequality between high- and low-skilled workers (Geishecker and Görg, 2011; Munch and Skaksen, 2009; Hummels et al., 2011; Amiti and Davis, 2012), and that low-skilled workers appear more vulnerable to import competition from low-wage countries (Autor et al., 2014). Results on the role of exports suggest that exporting activities contribute to increased wage premiums of high-skilled workers because their employer's internationalization allows them to bargain over higher profits (Baumgarten, 2013; Krishna et al., 2012; Helpman et al., 2017; Schank et al., 2007; Carluccio et al., 2014; Klein et al., 2013; Amiti and Davis, 2012). The literature on inward FDI in developed and developing countries finds that foreign-owned firms pay higher wages, on average, than privately owned local firms (see Girma and Görg (2007) for the United Kingdom, Huttunen (2007) for evidence on Finland, Lipsey and Sjöholm (2010) for evidence on Indonesia, Heyman et al. (2007) for evidence on Sweden and Feenstra and Hanson (1997) for evidence on Mexico). The existence of spillovers has been indicated as one of the reasons why inward FDIs might benefit a host economy. Imitation of technological innovation and worker mobility from foreign-owned to domestic firms may increase the productivity of other firms in the host country (Fosfuri et al., 2001).

dispersion appear to be relatively scarce.² Yet, foreign direct investment is an important contributor of the internationalization of firms.³

One of the reasons why companies engage in FDI is to protect specific know-how, technology and/or managerial knowledge within the company (Ramondo et al., 2016; Hortaçsu and Syverson, 2009). Therefore, compared to international subcontracting firms, multinational companies might transfer skill-intensive technology and skill-intensive production stages more intensely, which might affect skilled and unskilled workers differently. On the one hand, skilled-workers might suffer if the technology and the knowledge transferred are skill-intensive. On the other hand, FDI might increase the need for language, communication, and managerial skills in the home country (Laffineur, 2018). Hence, the specificity of outward FDI deserves further scrutiny to analyze the direction of its effect depending on worker skills.

In this article, we use a detailed employer-employee dataset for France, covering the period 2002–2007, that enables us to control for individual characteristics (sex, age, diploma, occupation) as well as those of firms (exports and imports, size, productivity, sector), in order to analyze the specific role of outward FDI on wage dispersion. We are able to account for various means of internationalization strategies, including imports of intermediate inputs, imports of finished goods, exports and outward FDI.

Our main results are the following. First, we observe that firms engaging in outward FDI (henceforth ‘multinational firms’) pay a wage premium to their employees, even within precise skill-groups (blue-collar, intermediate profession, managers). The wage premium increases within the wage distribution: the wage premium of multinational firms is 57% higher among high-paid workers than among low-paid workers. In a second step, by using the statistical framework of Abowd et al. (1999) (AKM hereafter), we find two interesting results. First, exports raise wages paid to blue-collar workers and intermediate occupations. Second, outward FDI significantly raises manager wages and reduces the wages of workers performing offshorable tasks. More precisely, we observe that investing abroad raises manager wages by 0.077%, which accounts for an average increase of € 3465 per year. Conversely, FDI reduces wages by 0.30% when the offshorability score increases by one unit.

We disentangle the results according to the type of firms: first-time investors (which we label extensive margin) and established multinationals (which we label intensive margin). The positive effect on manager wages is mainly driven by the intensive margin of outward FDI, that is by large firms already established abroad. The coefficient associated with FDI in the sample of established multinational firms is nearly five times larger than in the sample of first-time investing firms.

We also analyze the differentiated impact of FDI depending on the nature of the internationalization strategy, which can be horizontal or vertical. On the one hand, FDI can act as a form of offshoring if the creation and/or the acquisition of a foreign company allows firms to break up the value chain in several countries, which is often referred to as vertical FDI. On the other hand, outward FDI can be market-seeking and does not necessarily increase the fragmentation of the production process, which is often referred to as horizontal FDI. Market-seeking FDI should mostly affect domestic wages through its effects on the localization of profits and/or the bargaining process of wages.⁴ Our results show that the positive effect of FDI on manager wages is mainly driven by FDI in low income countries.

Finally, we identify the sources of wage dispersion induced by outward FDI. The literature has identified two sets of explanations for wage dispersion across firms. The first line of explanation lies in firm heterogeneity through rent-sharing mechanisms, that is to say, the most productive firms might have to pay higher wages to redistribute their profits in order to elicit full effort. Thus, multinational companies might rely more often on performance-based pay to elicit full effort, especially in companies where decision-making and management is decentralized (Bloom et al., 2010; Guadalupe and Wulf, 2010; Amiti and Davis, 2012).⁵ The second line of explanation lies in individual heterogeneity through labor market friction and differences in market values of workers’ unobservable skills (Helpman et al., 2010; Davidson et al., 2014; Egger and Kreickemeier, 2009). Because screening workers’ abilities is costly (publication of ads, search for candidates, conducting interviews), the most productive firms have a comparative advantage in more accurately screening worker abilities. The existence of screening costs implies that firms are willing to pay higher wages in order to avoid replacement cost of a higher ability workforce (Helpman et al., 2010). Hence, multinational firms might have a greater ability to screen workers and attract the best candidates.

Our results regarding the source of the wage premium show that firm heterogeneity through rent-sharing mechanisms plays a

² Some contributions have analyzed the characteristics of MNE in terms of employment and wages and the role of multinational investments on employment (e.g. Muendler and Becker (2010) and Becker et al. (2013)).

³ In the United States, roughly one-half of U.S imports are transacted within the boundaries of multinational firms rather than across unaffiliated parties (Bernard et al., 2009). In France, several reports stress that large multinational companies have favored internationalization through in-house foreign production, compared to German firms which have favored internationalization through arm’s length production (Fontagne and Toubal, 2010). According to the French office of statistics (Insee), French-owned multinational firms (approximately 3100 business groups) represented nearly 35% of total employment in French companies in 2011 (excluding the agriculture sector) and 57% of their total value-added. Therefore, outward FDI has potentially a large effect on French the working conditions and wages of French workers.

⁴ The extent to which domestic workers might benefit from their firm’s international expansion will depend on three parameters: (i) first, the share of foreign profits which are repatriated, which especially depends on tax rate and growth prospect differentials between the home and the foreign country. (ii) The second parameter is information asymmetries in the bargaining process, which might give an advantage to the employer as only the employer has the full information about the productivity of foreign plants and/or the share of foreign profits which are repatriated. Domestic workers lacking information about the firm’s profitability might lower their wage demands in order to increase the probability of acceptance, as argued by Creane and Davidson (2008). (iii) the third parameter is the importance of the “threat effect” (Choi, 2001). Employer ability to resort to foreign production increases their bargaining power in the wage negotiation because workers may fear to lose their jobs.

⁵ Based on Norwegian data, Barth et al. (2009) highlight the contribution of pay schemes based on individual output to the rise of within-firm wage inequality. Increasing foreign market competition seems to increase the use of performance-related pay within companies, as suggested by Cuñat and Guadalupe (2009). They show that a higher level of product market competition increases the performance-related component of compensation schemes for executives, but not for workers.

more important role in explaining multinational firms wage premium than labor market friction. Hence, the positive effect of outward FDI on manager wages comes from their greater ability to capture a firm's productivity gains.

The article is organized as follows. The next section describes the data and the main variables. Section 3 analyzes the results of the wage gap between multinational- and domestic-workers. Section 4 presents the methodology. Section 5 estimates the wage effect of FDI within job spells. Section 6 identifies the sources of the wage premium and Section 7 concludes.

2. The data

Our database is constructed with six micro-data sources. Three of them are employee-level databases (Déclaration Annuelles des Données Sociales (DADS), Échantillon Démographique Permanent (EDP), the French survey on working conditions). This data shares a common firm identifier in order to merge them with three other firm-level databases ("Liaison Financière" dataset (LIFI), customs data and "Enquête Annuelle Entreprise" (EAE)).⁶ As several changes have been conducted to improve these databases, we only provide detailed descriptions of the data for our period of observation (2002–2007).

2.1. Employee level information

The administrative panel—Déclaration Annuelles des Données Sociales—is built from confidential yearly social-security records, treated and transmitted by the French National Institute for Statistics (INSEE). Administrative records are based on firms' mandatory report of workers subject to payroll taxes to fiscal authorities. The database covers all firms in the private and public sectors. From this administrative record, a panel of individuals born in October is built. Each observation consists of an employer-employee match and reports the sex, age, residence and workplace-region, yearly real earnings (in 2007 euros) and the number of hours and days worked each year by the individual.⁷ The database allows the identification of three types of occupations: blue-collar workers (skilled and unskilled), managers, and intermediate occupations (secretaries, technicians and foremen).

As wages and careers are likely to be affected by personal events such as birth or marriage, we use data enhanced by information from the Permanent Demographic Sample ("échantillon démographique permanent", EDP). The Permanent Demographic Sample is augmented with variables from the annual census surveys. Currently, about 900,000 individual's social and professional trajectories are well tracked. The sample includes all the civil status and information from census surveys for individuals born on one of the first four days of October each year. This data source gives details concerning education, marital status, and number of children.

There is a scientific debate on whether wage inequality is driven by technological progress or globalization. In order to account for these two elements we build two indexes that capture the content of occupations. We measure their vulnerability (or substitutability) to technological progress by a measure on the use of computers and to globalization by an index on the offshorability of the tasks they perform.

Computer use. We use the French working condition survey produced by the French "Direction de l'Animation de la Recherche, des Etudes et des Statistiques" (DARES) in 2005. The inquiry is realized every seven years on a sample of 19,000 workers and measures several aspects of working conditions based on the statements of employees. We build an index reflecting the intensity of the use of computers at the occupation level. The index is derived from the yes/no question: "do you need to work, even occasionally, with a computer connected to a network or to other computers?". A negative answer is coded 0 whereas a positive answer is coded 1. The index is the ratio of the sum of answers over the total number of workers in a particular 2-digit occupation, such as $\frac{1}{n_{io}} \sum_i d_{io}$ where d_{io} is a dummy equal to 1 if the worker i answers 'yes' to the question on the use of computer and 0 if the answer is no. n_{io} is the total number of workers i in a particular occupation o . The more workers in a particular occupation that declare using computers, the higher the index is. Managers have an index of 0.905 (90% of respondents in the occupation of managers declared using a computer), engineers have an index of 0.931, administrative workers of 0.805, technicians of 0.799, foremen of 0.610, secretary of 0.805, skilled blue-collar workers of 0.311 and unskilled blue-collar workers of 0.206.

The use of computers is measured for 2005. We assume that it does not change over the period from 2002 to 2007. We attribute the same value if the worker does not change occupation. The index changes at the worker-level when the worker switches occupations.

Offshorability of tasks. We build a second task index in order to measure the routinization of occupations. We aim at providing an index that captures the routine nature of tasks, in order to classify occupations according to their offshorability. The index is built on nine specific questions about job activities, ranged according to their frequency.⁸ These questions are related to a number of items that capture the offshorability nature of the job. The questions relate to the need to physically interact with customers and suppliers. These interactive-intensive occupations would have a small likelihood to be offshored. On the other hand, there are questions on the routine nature of jobs whose tasks would be easier to relocate.

We weight each question such that the more routine an occupation is, the higher the score. For example, the answer "no" to the question "is your job imposed by the automatic movement of a machine" is coded 1, whereas the answer "yes" is coded 2 as it is more likely that occupations paced by the rhythm of a machine are more routine.

We map the index of offshorability to occupations in three steps. First, we sum the values attributed to each answer to the nine

⁶ We are really grateful to the CASD, the Genes (groupes des écoles nationales d'économie et de statistique) and the National Institute of French Statistics for having provided this data.

⁷ Workers in the DADS can be identified in several positions, we only keep the worker-firm match for which the job spell and salary is the highest.

⁸ More details about the construction of the index is given in [Appendix C](#).

questions for each respondent. Second, we calculate the average of the index for the 412 PCS-ESE 4-digit occupations. More formally, we map the index to occupations by measuring the average task index in a given PCS-ESE 4-digit occupation, such as $\frac{1}{n_{io}} \sum_i d_{io}$ where d_{io} is the sum of the values attributed to the nine questions and n_{io} is the total number of workers i in a particular occupation o .

Finally, we normalize by the maximum and minimum index value in any occupation so that the offshorability index varies between zero and one across occupations. With this standardization, each occupation is assigned a number between 0 and 1 that measures its degree of routine tasks.

The higher the index is, the more workers perform routine tasks. These workers are more likely to be vulnerable to offshoring. As for the computer-use index, the offshorability index is constant for each year between 2002 and 2007. The index changes at the worker-level when the worker switches occupations.

2.2. Firm level information

Firm level information comes from three confidential databases. The first one is the “*Liaisons Financières*” survey (LIFI), which collects all financial links involving at least one French firm and allows the identification of firms engaged in outward FDI (i.e. firms having 10% or more of voting stock in a foreign firm). We are able to identify both the firm’s parent company and the firm’s foreign subsidiaries. We sum the number of foreign subsidiaries in order to construct our FDI measure.⁹ We control our results by building a second measure of FDI capturing the number of countries where the firms owns at least one FDI. We also build a variable of vertical FDI, measured by the number of foreign subsidiaries to low-income countries and a variable of horizontal FDI, measured by the number of foreign subsidiaries to high-income countries.¹⁰

Second, we use a firm survey from the French Manufacturing Census, known as “*Enquête Annuelle Entreprise*” (EAE). This database provides the detailed income statements of all French manufacturing firms with more than 20 employees. The database allows for the controlling of several variables concerning the firm’s characteristics, such as tangible assets (in millions), revenue (in millions) and firm productivity. Firm productivity is approximated by a measure of total factor productivity which is derived from the approach of Levinsohn and Petrin (2003) which allows controlling for endogeneity, resulting from the correlation between unobservable productivity shocks and input levels. We use operating expenses as the proxy variable for productivity shocks, value-added as the dependent variable as well as the number of employees as a proxy of the labor force and the total fixed assets as a capital proxy.¹¹

Finally, the last database is derived from French customs and contains the amount of exports and/or imports by product (CN8 nomenclature) and by destination country for each year between 2002 and 2007. We distinguish imports of finished and imports of intermediate goods. Finished goods are defined as CN8 products that correspond to the same 3-digit NACE code of the main activity of the firm.¹² Other imported goods are defined as intermediate goods. Our measure of outsourcing is the share of imports of intermediate inputs and finished goods over the firm’s sales: $\frac{II_{it}^c}{T_{it}^c}$ and $\frac{TG_{it}^c}{T_{it}^c}$ respectively, with II_{it}^c corresponding to the firm’s i imports of intermediate inputs at time t from country group c , TG_{it}^c corresponds to the firm’s imports of finished goods at time t from country group c , and T_{it} the firm i sales at time t . We define two groups of countries: the group of high-income countries corresponds to high-income OECD countries (as defined by the OECD in 2007)¹³ and the group of low-income countries corresponds to all other countries.

Initially, the sample of the DADS covers all workers in private sector establishments, government owned establishments and hospitals. By merging these databases, we only keep employees in private-sector manufacturing firms with more than 20 employees, excluding the energy sector.¹⁴ We give a detailed descriptive statistics of principal variables for the pooled sample (in Appendix).

⁹ In order to interpret the variable we scale the variable of FDI by dividing it by 100.

¹⁰ High income countries are composed by EU-15 countries and Norway, Japan, Switzerland, the United States, Australia, Canada, New Zealand, Liechtenstein, Monaco, Gibraltar, Iceland, and Andorra, whereas other countries are considered as low-income countries.

¹¹ We have used different proxies for technological change, such as investment in R&D, proximity to the sector technological frontier and software investment. The proximity to the sector’s frontier represents the gap between the (log) productivity of a particular firm and the highest productivity (or the highest percentile productivity) in the same industry. The productivity of the firm is measured as the value added per worker such as: $Proximity_{ikt} = P^{95} \log\left(\frac{VA}{L}\right)_{kt} - \log\left(\frac{VA}{L}\right)_{ikt}$. We use the 95 order percentile in order to have a robust measure, by excluding outliers. The lower the variable is, the more productive the firm is. Our main conclusions do not depend on the proxy which is chosen.

¹² Correspondence tables exist between NC8 classification and the CPA classification (classification of products by activity) for which each product is associated to a single activity (NACE code).

¹³ countries whose per capita gross national income (GNI) has been above the World Bank graduation threshold (\$6275) for at least two consecutive years.

¹⁴ We also keep employees observed during a full year and those having a full-time contract. Furthermore, the Hausman test rejects the assumption of random attrition in the unbalanced panel sample. Hence, we run regressions on the balanced sample. However, results on the unbalanced sample report similar coefficient and standard errors of the main variables of interests so our conclusions remain unchanged. We do not present results on the group of administrative employees because we do not have enough observations.

Table 1
Variance analysis of log-wage change (2002–2007).

	2002	2007	Change
Between-skill groups	42.41	43.06	3.29
Within-skill groups	57.59	56.94	96.71
Between-occupations	26.27	31.15	6.78
Within-occupations	73.73	68.85	93.22
Between industries	1.62	1.35	0.07
Within industries	98.38	98.65	99.93
Between firms	62.37	62.19	56.75
Within firms	37.63	37.81	43.25
Within-occupations: between firms	62.50	61.53	57.41
Within-occupations: within firms	37.50	38.47	42.59

Reading: The share of the different components of variance analysis is given in %.

Note: The between- and within-firm component of within-occupation inequality has been obtained by calculating the residuals of a linear regression of log-wages over $age \times occupations$ dummies, and then calculating the within/between variance decomposition.

Source: LIFI survey, French annual census for manufacturing (EAE), French Déclaration annuelles des données sociales (Panel DADS-EDP); period: 2002–2007.

3. Preliminary findings

3.1. Source of wage inequality

A natural starting point for our analysis is to analyze trends in wage dispersion in the French manufacturing sector over the period 2002–2007.

We decompose wage dispersion, as measured by the variance of daily wages, into within and between components along different groups. We define four groups of analysis: by (i) skills, by (ii) occupations, by (iii) industries and by (iv) firms.¹⁵ We index workers by i and the different demographic groups by k such that the overall wage variance can be decomposed as follows:

$$\sum_{i=1}^p \sum_{k=1}^n (w_{ik} - \bar{w})^2 = \sum_{k=1}^n N_k (\bar{w}_k - \bar{w})^2 + \sum_{i=1}^p \sum_{k=1}^n (w_{ik} - \bar{w}_k)^2$$

Where overbars denote average of log hourly gross wages, k denotes a particular group and i the individuals. We run the analysis on wage variance for the year 2002, for the year 2007 and for wage differences between 2002 and 2007. The estimations are based on the sample of full-time, full-year workers, working in the manufacturing sector.

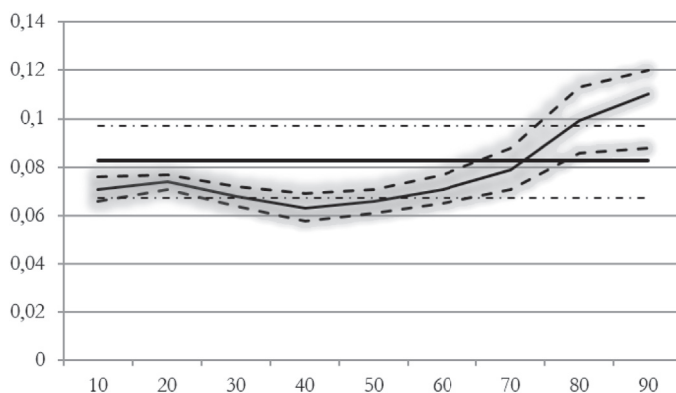
Table 1 reports the contribution of within- and between-components of total wage variance (in %). Each line reports the results for the decomposition along the different components of skills, occupations, industries and firms. Column (1) reports the results for the decomposition of the variance of wage between- and within skill-groups. The analysis underscores that 42.1% of wage variance arises between skill-groups and 57.59% occurs within skill-groups, which is very similar to what is obtained with German data (Baumgarten, 2013; Faggio et al., 2010).¹⁶ The second line of Table 1 reports the results of the decomposition between- and within-occupations. Most of the variance of wage dispersion between 2002 and 2007 is explained by within-occupations components (93.22%). Thus, analyzing inequality between occupations is less relevant than analyzing wage dispersion within occupations. The third line accounts for the contribution of wage variance within- and between-industries. Only 1.62% and 1.35% of wage variance in 2002 and 2007 respectively accounts for differences between industries. Hence, aggregate data at the industry level may not capture the sources of wage inequality.¹⁷ Finally, the last two lines of Table 1 account for the contribution of wage variance between- and within-firms. Roughly 62% of wage variance in 2002 and 2007 accounts for differences between-firms (i.e. differences in firm characteristics) and most of the wage differential between 2002 and 2007 within-skill groups is explained by between-firm elements. However, the contribution of within-firm component is still substantial. 37.5% of total variance within-occupations in 2002 and 38.47% in 2007 occurs within-firms.

These results underscore the need to identify between-firm and within-firm wage differentials rather than providing an analysis at the industry level. Hence, we provide a first step in this direction by reporting the mean raw wage according to a firm's international status, within each group of occupations (See Table A.2 in Appendix A). The preliminary results highlight a wage premium for workers employed in large multinational companies compared to other workers. The average wage premium is partly due to a

¹⁵ We follow Baumgarten (2013) in defining skill and occupation groups as 40 age* education cells and 20 age* occupations cells. Education and occupations are described in Table A.1 Appendix A. We define five groups of age starting with one window of workers between 18 and 25 years, then 4 windows of 10 years each starting from 25 until 65 years old.

¹⁶ In contrast, results on Brazil highlighted the growth of wage inequality within sector-occupations to be almost entirely explained by wage inequality between firms. Here, in contrast, the within-firm component of wage inequality is not dominant but still account for 42.59% of the variance.

¹⁷ As mentioned above, some articles however suggest that looking at intra-industry effects leads to underestimating the effects of offshoring on wages: the most significant wage cuts would occur when displaced workers are forced to switch industries (Ebenstein et al., 2014; Baumgarten et al., 2013).



Source: LIFI survey, French annual census for manufacturing (EAE), French Déclaration annuelles des données sociales (Panel DADS-EDP); period: 2002–2007.

Note: The figure shows coefficients associated with the number of foreign affiliates for 9 different hourly wage deciles, measured by quantile regression estimator over the pooled sample and its 95% confidence interval (dashed line).

Fig. 1. Estimated FDI coefficient by quantile of wage.

different skill-composition within multinational firms. For each occupation category, the share of workers with a professional college or university degree is higher among multinational firms, stressing their ability to attract the best workers (Table A.3 in Appendix A).

In order to gain deeper insight into the multinational firm wage premium along different groups, we apply a quantile regression of Mincer equations to consider adjusted wages at different points of the wage distribution. The model used is the following:

$$D_k(w | X_{ij}) = \beta_1 F_j + \beta_2 X_{ij} + u_{ijt} \quad (1)$$

Where X_{ij} are worker and firm characteristics as detailed previously. k represents the decile's number and i and j denotes workers and firms respectively. F_j is a dummy variable that equals one if the worker is employed in a multinational firm and zero otherwise.

Estimations are realized for each decile of the distribution of the conditional log hourly wage. β_2 denotes how the specified decile changes with one-unit change in X_{ij} . β_1 compares the k th decile of the log hourly wage distribution of workers employed in multinational firms (conditionally to all other variables) with the k th decile of the log hourly wage distribution of workers employed in domestic firms (conditionally to all other variables). We report the results for the coefficients associated with our variable of interest measuring the international status of the firm (Fig. 1).

The Figure also reports the results of OLS regression on the pooled-sample in order to depict the mean raw wage difference between individuals employed in a multinational firm and those employed in a domestic firm.¹⁸

The log wage premium for being employed in a multinational firm is around 0.08 log-wage during the period of observation. There is a wage premium within each occupation group, as shown by Fig. A.1 in Appendix A.¹⁹

The wage premium of workers employed in multinational firms is observed for each decile of the wage distribution, but those differences are higher in the upper and lower deciles of the low wage distribution, conditionally on other characteristics, shaping a polarized curve. The 9th decile of the log wage distribution of multinational workers is higher of 0.11 log hourly-wage. The 4th decile has the lowest difference (around 0.06 log-hourly wage), whereas the first two deciles have a difference of around 0.07–0.08 log hourly wage. When comparing the wage premium between the first and ninth quantile we observe that the wage premium of multinational firms is 57% higher among high-paid workers than among low-paid workers.

3.2. Understanding the multinational premium

In this section we first aim at giving descriptive evidence for the sources of the multinational firm wage premium. We assume that the same characteristics observed regarding multinational workers and domestic workers can receive different remunerations. The section then proceeds by decomposing the wage premium into one part due to the difference in the characteristics (observed by the econometrician) and into another part due to the different returns reserved to domestic and multinational workers (unobserved by the econometrician).

¹⁸ In order to allow for comparison between the average wage premium and the results for each decile of the wage distribution, we estimate a regression that accounts for the same worker and firm characteristics X_{ij} as in equation (1) and the same binary variable F_j that takes the value of one if worker i is employed in a multinational firm and zero otherwise. The regression is the following: $\ln w_{ij} = \beta_1 F_j + \beta_2 X_{ij} + u_{ijt}$.

¹⁹ We distinguish four groups of occupations: managers include engineers and executives; employees include administrative employees and commercials; intermediate occupations include administrative intermediates (accountants, technicians or foremen); and blue collar workers. These categories are defined by INSEE and are summarized in Table A.1 in Appendix.

Table 2
Contribution of explained and unexplained components of the raw-wage gap.

	All	Blue collar	Managers	Intermediate
Average log-wage of Multinational-workers	2.876*** [0.004]	2.656*** [0.004]	3.425*** [0.006]	2.925*** [0.005]
Average log-wage of Domestic-workers	2.672*** [0.003]	2.548*** [0.003]	3.290*** [0.007]	2.830*** [0.004]
Raw log-wage gap	0.205*** [0.005]	0.108*** [0.005]	0.135*** [0.010]	0.095*** [0.006]
Differences in returns to characteristics	0.019*** [0.005]	0.021*** [0.005]	0.077*** [0.011]	0.012* [0.007]
Differences in characteristics	0.186*** [0.004]	0.087*** [0.004]	0.058*** [0.009]	0.082*** [0.005]
Advantage of Multinational-workers	0.010	0.010	0.037	0.06
Disadvantage of Domestic-workers	0.010	0.010	0.037	0.06

Robust standard error in brackets, ***p < 0.01, **p < 0.05, *p < 0.10.

Source: LIFI survey, French annual census for manufacturing (EAE), French Déclaration annuelles des données sociales (Panel DADS-EDP); period: 2002–2007.

We use a variant of the [Blinder \(1973\)](#) and [Oaxaca \(1973\)](#) method (OB method) to decompose mean differences in log hourly wages between the group of workers employed in a domestic firm (group d) and those employed in a multinational firm (group m). The traditional well known OB method decomposes the difference in the linear prediction at the group-specific means of the regressors into two components: a component of the wage differential attributable to group differences in the predictors (endowment effect) and a second component attributable to the contribution of differences in the coefficients (return effect). The model is the following²⁰

$$\ln w_i = \gamma_0 + \gamma_{0m} M_i + \gamma_{0d} D_i + \gamma X_i + v_i \quad (2)$$

D_i is a dummy equal to 1 if the worker is employed in a domestic firm and $M_i = 1 - D_i$, which represents a dummy equal to 1 if the worker is employed in a multinational firm. X_i is a $1 \times K$ vector of explanatory variables and β is a $K \times 1$ vector of coefficients. Our explanatory variables are worker characteristics, such as sex, age, level of education,²¹ marriage, number of children. We also control for firm time-varying characteristics such as the skill composition of the firm, the industry, the value of exports (in millions €), the share of imports of intermediate inputs and finished goods over total sales, revenue (million K €), capital (in millions €), and the firm's total factor productivity as detailed in [section 2](#).²²

The raw log wage gaps are presented in [Table 2](#). Column (1) reports results for the entire sample, column (2) for the sample of blue collar workers, column (3) for the sample of managers and column (4) for the sample of intermediate occupations.

The results show that the mean of log-hourly wages for workers employed in multinational firms is 2.876 and 2.672 euros for workers employed in domestic firms. The raw log-wage gap (0.205) is presented in the third row. About 90% of the log-wages differences between the two groups of workers is attributable to differences in characteristics in the whole sample, meaning that domestic workers would have a 0.186 log wage increase if they had the same characteristics as multinational workers.

On the contrary, differences in return to characteristics account for 10% of the wage gap, meaning that domestic workers would have a mean increase of 0.019 log points if they had the same coefficient (return to characteristics) as multinational workers.

The contribution of the endowment and coefficient effect is not the same in each group of occupations. When splitting our results into three groups of workers according to their occupation (managers, blue-collar workers and intermediate occupations mainly composed of foremen and technicians), the unobserved (positive) discrimination of being employed in a multinational firm is 0.021 log-points in the sample of blue-collar workers and 0.077 log-points in the sample of managers. Return to characteristics,

²⁰ As pointed by [Oaxaca and Ransom \(1994, 1999\)](#), the group wage gap explained by differences between group characteristics is not invariant to whether one of the groups is chosen as the reference wage structure and an assumption has to be made as regards the direction of discrimination against one of the groups only. In this particular case, assuming that discrimination is only directed against domestic-workers and that there is no positive discrimination of multinational-workers is a strong assumption. A solution, following [Fortin \(2006\)](#), is to use a pooled wage regression that simply includes a dummy for the disadvantaged group. We run the analysis on the balanced panel data by excluding foreign owned firms. The hausman test reports significant differences between the balanced panel model and the unbalanced model, we therefore decide to report the results on the balanced model. However, in both case our principal conclusions are not altered. Furthermore, we do not include a dummy variable associated with the group nationality, as reported in [Table D.8](#), because there is not enough variance to estimate this variable: only 123 observations have changed nationality in the group of intermediate occupations, 73 in the group of managers and 256 in the group of blue-collar workers. To avoid capturing wage differences due to foreign-owned firms, we only focus on French groups. Indeed, the most productive firms within an industry tend to be the targets of foreign acquisitions ([Blonigen et al., 2014](#); [Arnold and Javorcik, 2009](#)). Hence, the non-inclusion of firm nationality would result in an endogeneity problem because the most productive firms also pay higher wages. However, results without the restriction to French groups gives very similar conclusions.

²¹ The assignment of the explained part of the wage gap to categorical variables is not invariant to the choice of the left-out category ([Fortin, 2006](#); [Gardeazabal and Ugidos, 2004](#)). To circumvent this problem, we follow [Fortin \(2006\)](#), by imposing a zero-sum restriction on the estimated coefficients of each categorical variable, where we impose $\sum_{j=1}^k \beta_j = 0$, where k is the number of categories for variable j , which can be implemented by restricted least squares. The shortcoming of this method is that it leaves the estimation of dichotomous variables without a simple meaningful interpretation. In our case, it is not a problematic issue, since we are not interested in the coefficients associated with worker and firm characteristics.

²² We have run several collinearity diagnostics between imports of intermediate inputs and foreign direct investment and between revenue, capital and TFP but there seems to be no multicollinearity problem in our estimations. Moreover, we do not include the variable measuring the use of computer at the worker levels since it is highly collinear to the skill-composition of the firm in the whole sample.

i.e. differences attributed to the unobserved part of the wage difference, account for a larger share of the wage gap in the sample of managers than in the sample of blue-collar workers. The unexplained part of the wage gap in the sample of blue-collar workers and intermediate occupations is relatively small, highlighting the strong effect of workers and firm characteristics in explaining the raw log wage gap. This indicates that returns to characteristics is very different in each group of occupations. The wage difference due to return to characteristics is particularly important in the sample of managers which reflects the important role of unobserved components in explaining wage differences between managers employed in a multinational firm and managers employed a domestic firm.

There are two possible explanations of the wage gap between multinational and domestic workers. First, a higher ability of workers to capture firm's rents in multinational firms and second, higher ability of multinational firms to use their revenue to attract the best workers. The next section describes the methodological steps needed to identify those two potential sources of wage gap.

4. Methodology

4.1. Identifying the multinational wage gap

Our goal is to estimate the impact of outward FDI on wages within each group of occupations. The AKM (1999) framework allows the decomposition of information on individual worker wages into individual and firm heterogeneity as well as time varying firm and individual characteristics. It allows the estimation of unobserved time-invariant person and firm effects. The model is as follows. Let $j(i, t)$ be a function indicating the firm at which worker i is employed at time t . We propose the following model for wages, where we include time dummies in the vector of covariates:

$$y_{ijt} = x_{it}\beta + x_{j(i,t)t}\tau + \theta_t + \psi_{j(i,t)} + \epsilon_{ijt} \quad (3)$$

Where y_{ijt} is the logarithm of real hourly gross wage of worker $i = 1, \dots, N$ in firm $j = 1, \dots, J$ in period $t = 1, \dots, T$. θ and ψ are person and firm fixed effects respectively. Person effects are common to all the employment spells of one individual whereas firm effects are common to all employees of the same firm (which can be assimilated as the firm's wage premium).

x_{it} is a vector of individual characteristics at time t and $x_{j(i,t)t}$ a vector of firm characteristics the individual is employed in.

Our variable of interest in the vector $x_{j(i,t)t}$ is outward FDI. The coefficient estimate measures the correlation between FDI and wages for different occupational level. The effect is identified when the firm invests in a new affiliate abroad. Among the 919 multinational firms in our sample, 428 of them changed their number of affiliates over the period 2002–2007. The investment can be a first-time investment (we call this extensive margin) or another investment by setting up additional affiliates (we call this intensive margin). One should note that the coefficient is only estimated for employed workers and does not tackle the employment adjustment margin which might also affect workers when firms change their internationalization strategy.²³

We estimate various specification of equation (3) for different occupation groupings and tasks. We test the robustness of our results, by using different proxies of firms' outward FDI (number of countries deserved, number of affiliates, dummy variable of being a multinational company).

A key condition for equation (3) to give consistent estimates is that the unobservable component ϵ_{ijt} is uncorrelated to our variable of interest. Our results could be biased if the decision of engaging in outward FDI is jointly determined with wage settings, or if unobserved variables affect simultaneously outward FDI and wage determination. Following Baumgarten et al. (2013), we test the exogeneity of our FDI measure by using a methodology inspired by Blundell and Bond (2000), which consists in using lagged values as instruments. Table B.5 in Appendix B reports the results of relevant post-estimation tests when we use the lagged values of the number of FDIs as instruments (with a lag of one and two years). The Hansen-J stats indicates that our instruments are orthogonal to the error term. Orthogonality conditions are not sufficient for an instrument to be good, it also needs to be correlated with included endogenous variable. The rk and F-test of joint significance of instruments in the first-stage regression reveal that our instruments are sufficiently strong.

We are unable to reject the exogeneity assumption and the variable FDI may not be treated as endogenous. The use of two instruments yields the loss of two observations per individual. We have checked the robustness of this result when using a one-year lagged value as an instrument and obtain similar statistics. However, we prefer to report statistics with two instruments (one-year and two-year lags) as it allows the checking of the validity of the instruments.

4.2. Endogeneous sorting

Another key condition for equation (3) to provide consistent estimates is that residuals ϵ_{it} are orthogonal to firm and person effects, which is:

$$E[\epsilon_{it} | x_{it}, x_{j(i,t)t}, u_i, q_{j(i,t)}, \alpha_i, \phi_{j(i,t)}, \mu_t] = 0$$

This condition implies that the unobserved component of wages does not predict worker mobility decisions. This condition is violated when the work-firm assignment is not random, i.e when unobservable characteristics of the match between worker i and

²³ Employment margin of globalization is also important, see for example Becker et al. (2013) and Laffineur and Mouhoud (2015).

firm j are correlated with the explanatory variable, such that worker mobility is endogenous.²⁴

The issue of endogenous assignment of workers to firm can be tackled by adding worker-firm match fixed effect in equation (3), as in Woodcock (2008). The match effect model accounts for the fact that worker mobility can be endogenous because the match between high productive workers and high productive firms might be driven by unobserved abilities. The empirical specification is similar to equation (3) where a term ϕ_{ij} is added and represents the returns to unobserved time-invariant characteristics of worker-firm matches, such as:

$$y_{ijt} = x_{it}\beta + x_{j(i,t)}\tau + \theta_i + \psi_{j(i,t)} + \phi_{ij} + \epsilon_{ijt} \quad (4)$$

Identifying workers, firms and match effects is cumbersome, especially because differentiating by workers does not provide the same result as LSDV.²⁵ We therefore decide to adopt the technique of Krishna et al. (2012) by time-demeaning covariates over the match firm-worker combination in order to compare results of the worker-firm model with the ones of the match effect model. The inclusion of these effects obviates the need to separate firm and workers fixed effects, but does not allow to identify firm, workers and match heterogeneity.

We follow Card et al. (2013) to test the separability assumption in the AKM model. We find coefficients, overall R-squared and Root MSE to be very similar in the match effect and AKM model, giving high confidence that the AKM assumption is roughly met (see Table B.6).

4.3. Identifying the sources of the wage premium

There are two sets of explanations justifying the wage premium of multinational firms. On the one hand, multinational firms may be able to create a larger surplus than domestic firms, which gives stronger opportunities for bargaining over the firm's profit, and thus some workers might benefit from higher rents, independently from worker characteristics (firm effect). On the other hand, international firms may be able to screen workers with higher unobserved (to the econometrician) skills (worker effect).

From equation (3), we retrieve unobservable firm and worker characteristics through estimation of the firm fixed-effect (ψ_{jt}) and worker fixed effect (θ_{it}). The firm fixed effect is a good proxy for the rent sharing effect, and the worker fixed effect, which captures worker ability, is a good proxy for the firm's ability to attract the best workers.²⁶

The estimation of worker and firm fixed-effect can be identified only with worker mobility between firms. Firm dummies are not different from any multicategory dummy, therefore, as long as workers can move from one firm to another over time, the firm dummy can be identified. Then, the person fixed effect $\hat{\theta}_i$ can be recovered as follows: $\hat{\theta}_i = \bar{y}_i - \bar{x}_i\hat{\beta} - \bar{x}_{j(i)}\hat{\gamma}$.

Hence, prior to estimation, we identify a group of “connected” workers and firms. There are 9222 workers in our sample, of which 6.60% are movers (609 workers).

We follow Macis and Schivardi (2016) in identifying the rent sharing and skill-composition effects. We define a skill composition (SC) term as the average worker effect at the firm-year level such as $SC_{jt} = \frac{1}{n_{jt}} \sum_i d_{ijt}\theta_{it}$ (d_{ij} is a dummy equal to 1 if the worker i is in firm j at date t and n_{jt} is the total number of workers in firm j at date t), and a rent sharing effect as the firm-year effect such that $RS_{jt} = \psi_{jt}$. The firm fixed effect can be seen as a wage premium paid to all employees in the firm whatever their characteristics and the worker fixed effect can be seen as worker-specific abilities whatever the firm fixed effect.

5. Foreign direct investment and worker-level wages

5.1. Baseline results

Table 3 displays estimation results from equation (3). We control for unobserved worker heterogeneity in the form of individual fixed effects. Workers' fixed effects are collinear with education and gender variables, so these variables cannot be included in the model. Similarly, the age and tenure effects are absorbed by the time dummies, hence age squared is the only individual-level variable that can be included when controlling for unobservable and time invariant individual characteristics. We add time varying individual characteristics such as the number of children and a dummy indicating if the worker is married. We also control for unobserved firm heterogeneity in the form of fixed effects, and add firm's time-varying characteristics (sales, capital, total factor productivity, exports, imports), as described in section 3.

We are interested in the impact of outward FDI on domestic wages within occupations for the whole sample (column (1)). We divide our sample into four main occupations: managers (column (2)), blue-collar workers (column (3)) and intermediate occupations

²⁴ This hypothesis of job assignment based on unobservables has been explored theoretically. Helpman et al. (2010) assume heterogeneous firms and heterogeneous workers in their unobserved productivity. They show that the most productive workers are employed in the most productive firms and receive higher wages. Egger and Kreickemeier (2009) build a model in which workers have bargaining power and prefer being employed in more productive firms because they pay higher wages.

²⁵ To circumvent this problem, Woodcock (2008) estimates a mixed model in the spirit of Hausman and Taylor (1981) which estimates β using the within-match estimator and allows for a relationship between individual and firm heterogeneity.

²⁶ One crucial concern when attempting to estimate the fixed effects is that worker mobility decisions are independent of ϵ_{it} . If this is not the case, the firm/worker match is not random conditional on observables and time-invariant unobservables. According to section 4.2 we are confident that adding a match specific component yields only a small improvement in the fit of the model. We thus retrieve worker and firm-fixed effect from the AKM specification (Davidson et al., 2014; Macis and Schivardi, 2016).

Table 3
Person and firm effect model.

	All	Managers	Blue-collar Workers	Intermediate Occupations
Number of FDI abroad	0.029** [0.012]	0.077*** [0.023]	0.013 [0.027]	0.008 [0.016]
Revenue	0.012*** [0.004]	−0.000 [0.013]	0.024*** [0.007]	0.018*** [0.006]
Capital	0.012* [0.006]	−0.005 [0.014]	0.018 [0.012]	0.009 [0.009]
TFP	0.006 [0.006]	−0.009 [0.016]	0.012 [0.009]	−0.000 [0.000]
Imports of II	−0.000 [0.000]	−0.000 [0.000]	−0.000 [0.000]	−0.001 [0.001]
Imports of FG	0.000 [0.000]	0.000 [0.001]	−0.000 [0.001]	0.001*** [0.000]
Exports	0.027*** [0.005]	0.009 [0.013]	0.044*** [0.009]	0.012* [0.007]
Computer Use	0.068*** [0.007]	−0.062 [0.004]	0.007 [0.045]	−0.030 [0.030]
Age-squared	−0.047*** [0.002]	−0.063*** [0.005]	−0.040*** [0.003]	−0.049*** [0.003]
Number of children	0.001 [0.002]	−0.001 [0.007]	0.003 [0.004]	−0.005 [0.004]
Marriage	−0.003 [0.006]	−0.034** [0.016]	0.012 [0.009]	−0.018** [0.008]
Observations	48,234	9144	23,867	15,223
R-squared	0.103	0.120	0.076	0.131
Number of person-firms	11,134	2318	5961	4123

Robust standard error in brackets, ***p < 0.01, **p < 0.05, *p < 0.10.

Source: LIFI survey, French annual census for manufacturing (EAE), French Déclaration annuelles des données sociales (Panel DADS-EDP); period: 2002–2007.

(column (4)). We run the regression separately for each occupation as each regressor might have a differentiated impact on wages depending on the type of occupation.

We first look at the coefficients of controls. Hourly wages appear to decrease when workers get married. This result is mainly driven by intermediate professions and managers (column (2) and (3)). These results might reflect either a lower propensity of workers to devote significant effort towards their careers the year following their marriage, or a lower propensity for employers to give them additional responsibilities. Changes in the number of children are not found to affect hourly wages. The age-squared variable has also a negative and significant coefficient for all occupations, reflecting a decreasing return of seniority on wages.

Looking at firm controls, hourly wages increase with firm productivity, especially for blue-collar workers.²⁷ Increasing tangible assets has a positive and significant effect on blue-collar worker wages: these workers might need to develop new skills when their company invests in new machines and tools and this might improve their bargaining power in wage negotiations. The coefficient associated with the level of exports is also highly significant, and this result is obtained in each sub-sample except managers, highlighting a wage-premium associated with exports. Conversely, imports are not found to affect domestic wages, whether we consider imports of intermediates or imports of finished goods in the sample of blue-collar workers and managers. In the sample of intermediate occupations, imports of finished goods have a positive effect on their wages.

Our variable of interest is the measure of outward FDI. In our base regression, we account for outward FDI with the number of foreign affiliates. This variable has a positive and significant effect on wages, but only when we restrict the sample to managers. Considering the number of countries where the firm owns foreign affiliates, instead of the number of foreign affiliates, provides similar results (Table D.7 in Appendix D). As argued above, the positive effect of outward FDI on manager wages might reflect several mechanisms. First, the creation of affiliates abroad might come with greater responsibilities for managers in the parent company, such as supervising and monitoring new entities or managing cultural and linguistic differences. These additional skills and responsibilities might translate into higher wages. Second, managers might be in a better position than other employees to capture productivity gains associated with outward FDI. The magnitude of the effect of FDI on manager wages is quite substantial. An increase of one foreign subsidiary raises annual manager wages by 0.077%. For managers who earn an average yearly net wage of roughly € 45,000 in 2007 an increase in the firm's foreign affiliates raises annual manager wages by € 3,465²⁸

²⁷ One should note that we have used several other proxies for technological change at the firm level, such as proximity with the firm's technological frontier, investment in R&D or value added per worker. Main conclusions remain unchanged.

²⁸ The coefficient is higher in France than in Denmark, where Hummels et al. (2014) find a coefficient of 0.0371 for high skilled workers. One should note that they measure offshoring by imports and we do not find any effect on imports.

Table 4

Person and firm effect model: discrimination on offshoring destination.

	All	Managers	Blue-collar workers	Intermediate Occupations
Number of FDI to LI	0.054 [0.040]	0.173** [0.078]	−0.041 [0.082]	0.018 [0.054]
Number of FDI to HI	0.011 [0.032]	−0.004 [0.064]	0.054 [0.059]	−0.002 [0.047]
Revenue	0.013** [0.004]	0.001 [0.001]	0.002* [0.001]	0.002*** [0.001]
Capital	0.011** [0.006]	−0.000 [0.002]	0.003** [0.001]	0.001 [0.001]
TFP	0.000 [0.000]	−0.000 [0.000]	0.000** [0.000]	−0.000 [0.000]
Imports of II	−0.000 [0.000]	−0.000 [0.000]	−0.000 [0.000]	−0.001 [0.001]
Imports of FG	0.000 [0.000]	0.000 [0.001]	−0.000 [0.001]	0.001*** [0.000]
Exports	0.027*** [0.005]	−0.005 [0.014]	0.047*** [0.009]	0.015** [0.007]
Constant	3.775*** [0.038]	4.401*** [0.106]	3.180*** [0.045]	3.970*** [0.066]
Observations	48,234	9144	23,867	15,223
R-squared	0.103	0.120	0.076	0.131
Log Likelihood	51324.325	9225.547	25716.706	18778.665

Source: LIFI survey, French annual census for manufacturing (EAE), French Déclaration annuelles des données sociales (Panel DADS-EDP); period: 2002–2007.

Note: The regression includes individual-level controls such as number of children, marriage, computer use and age-squared. The full Table is available in the online appendix on the author's web page. Robust standard error in brackets, ***p < 0.01, **p < 0.05, *p < 0.10.

5.2. Additional results

We test for a differentiated impact of outward FDI depending on the level of technology inside the industry.²⁹ We observe that for managers, the coefficient associated with outward FDI is nearly eight times higher when we restrict the sample to high-technology industries. Intermediate occupations in high-technology industries also experience a positive effect of outward FDI, whereas we do not observe this effect for low-technology industries. The choice to make a foreign direct investment in high-technology intensive industry may be related to the will to maintain an ownership advantage. Indeed, technology intensive firms are more likely to engage in outward FDI rather than arm's length transactions in order to avoid technology leakages. The transfer of firms' specific technology to foreign units may increase the wage paid to some workers at home, in particular those whose skills complement the ones in the foreign subsidiary. This idea is related to the skill-biased technological change that increase the wage premium of skilled workers. Transfer of technology-intensive production may increase the wages paid to workers, whose jobs require technology and communication skills. This assumption has been validated in the United States, to explain the role of technological progress on the evolution of wage inequality (Acemoglu and Autor, 2011; Goos and Maning, 2007; Firpo et al., 2011; Autor et al., 2006; Autor and Handel, 2013).

We now investigate whether the positive effect of outward FDI on domestic wages is driven by the extensive margin of outward FDI (meaning domestic firms which decide to go multinational) or by the intensive margin (multinationals which change their number of foreign affiliates). In order to focus on the impact of outward FDI at the extensive margin, we change our FDI measure and use a dummy indicating if the firm has foreign affiliates or not (rather than the number of foreign affiliates). Results in Table D.10 in Appendix D suggest that the effect of outward FDI at the extensive margin is lower: managers experience a wage increase when their firm goes multinational, but the magnitude of the effect is smaller than in the base regression. However, we observe that a change in the firm's international status, from domestic to multinational companies has a positive effect on intermediate occupations' hourly wages, which was not observed in the base specification.

We now look at the effect at the intensive margin by restricting the sample to employees which always belong to a multinational firm during the whole period (measuring outward FDI with the number of foreign affiliates, as in the base regression). This time, results are very similar to results in our base regression (see Table D.10) in the sample of managers, which highlights that the effect of outward FDI is mostly driven by the intensive margin. In order to check whether our results are driven by some large multinationals which open affiliates overseas, we run our base regression on the sample restricted to firms with less than five foreign affiliates: the coefficient associated with the number of foreign affiliates was found to be non-significant (see Table D.9 in Appendix D), suggesting that the positive effect of outward FDI on domestic wages only becomes visible in very large multinational corporations.

As argued in the introduction, the nature of the underlying mechanisms should differ according to the nature of FDI (vertical versus horizontal). This is why we distinguish the number of foreign affiliates according to their location: low income countries or high income countries. We notice that the positive effect of outward FDI on manager wages is mainly driven

²⁹ Details about the division of low-tech and high-tech industries are given in Appendix D.2.

Table 5
Person and firm effect model: Task offshorability index.

	(1)	(2)
FDI	0.004 [0.016]	
FDI to LI countries		−0.000 [0.000]
FDI to HI countries		0.000 [0.000]
FDI*Offshorability	−0.340*** [0.127]	
FDI LI*Offshorability		−0.768* [0.408]
FDI HI*Offshorability		−0.015 [0.313]
Offshorability index	−0.096*** [0.031]	−0.095*** [0.031]
Constant	3.844*** [0.044]	3.844*** [0.044]
Observations	48.234	48.234
R-squared	0.104	0.104
Log Likelihood	51336.803	51335.853

Source: LIFI survey, French annual census for manufacturing (EAE), French Déclaration annuelles des données sociales (Panel DADS-EDP); period: 2002–2007. We also control for the same variables as in Section 5.1 and 5.2 (revenue, capital, TFP, imports of intermediate inputs, imports of finished goods, computer use, age squared, exports, number of children, and marriage). The detailed results are available upon request. Robust standard error in brackets, ***p < 0.01, **p < 0.05, *p < 0.10.

by FDI in low income countries (see Table 4). One potential explanation is that emerging economies offer greater growth prospects and/or constitute ideal locations for offshoring. Therefore, investments in low-income countries might allow managers to bargain on higher profits. Another explanation could be that managing affiliates in low-income countries is more demanding (necessity of implementing new technologies or new managerial methods in the affiliate) and implies more complex tasks.

5.3. Task decomposition

Skilled workers and unskilled workers are no longer considered to be two homogeneous groups who have suffered the same impact following the adoption of new technologies or intensification of world trade. Job content of occupations becomes a central component to analyze the labor market with a new eye. This section investigates this question empirically by analyzing the wage effect of offshoring depending on the nature of tasks carried out by workers.

Different criteria have been used to define offshorable tasks. According to Autor et al. (2003) (ALM hereafter), the degree to which one task is codified determines its potential of relocation. The more a task is determined by specific rules, the less it relies on tacit knowledge and the easier it is to explain this task to someone else and to control it. According to Blinder and Krueger (2013), the offshorability of a task depends on its potential to be realized in another location without loss of quality and also on the importance of face-to-face interactions with people other than fellow workers.

We build a task index derived from a French survey on working conditions as detailed in section C. The higher the index is, the more workers perform routine tasks and the easier it is to relocate these occupations³⁰. The offshorability index is included in an interactive way in order to identify a non-monotonous wage change along the wage distribution (Autor et al., 2003; Oldenski, 2012).³¹

$$y_{ijt} = x_{it}\beta_1 + \text{Offshorability}_{it}\beta_2 + \text{FDI}_{j(i,t)}\gamma_2 + x_{j(i,t)}\gamma_1 + (\text{Offshorability}_{it} \times \text{FDI}_{j(i,t)})\beta_3 + \theta_i + \psi_{j(i,t)} + \epsilon_{ijt} \quad (5)$$

The regression coefficients *Offshorability* and *FDI* are in a conditional relationship, i.e. they reflect the change of one coefficient when the other is set to zero. Studies often center variables in order to make the results more interpretable, by comparing the effect of one variable compared to the average level of the other. The index varies between zero and one. A value of one represents a routine-intensive occupation whereas a value of zero represents an interactive- and analytic-

³⁰ We have also run the regression based on an index developed from the ONET databases. The results are very similar when using this index. In particular, the interaction term between FDI to low-income country and the offshorability index is significant at the 5% level. Tables are available upon request.

³¹ The offshorability index is constant if a worker does not change occupation. However, the classification PCS-ESE is sufficiently detailed to have 41.5% of workers that change occupations and thus change the offshorability index.

Table 6

Wage-regression capturing the productivity effect.

	All	Managers	Blue-Collar Workers	Intermediate Occupations
Number of children	0.001 [0.002]	−0.001 [0.007]	0.002 [0.004]	−0.005 [0.004]
Marriage	−0.003 [0.006]	−0.034** [0.015]	0.012 [0.009]	−0.018** [0.008]
Number of FDI abroad	0.024 [0.017]	0.101*** [0.032]	0.004 [0.033]	0.002 [0.025]
Age-squared	−0.047*** [0.002]	−0.063*** [0.005]	−0.040*** [0.003]	−0.049*** [0.003]
Exports	0.040*** [0.005]	0.004 [0.009]	0.044*** [0.009]	0.031*** [0.004]
Year fixed effect	Yes	Yes	Yes	Yes
Observations	48,234	9144	23,867	15,223
R-squared	0.1001	0.121	0.076	0.131
Number of person-firms	11,134	2318	5961	4123

Robust standard error in brackets, ***p < 0.01, **p < 0.5, *p < 0.10.

Source: LIFI survey, French annual census for manufacturing (EAE), French Déclaration annuelles des données sociales (Panel DADS-EDP); period: 2002–2007.

intensive occupation. We thus center our second offshorability index by using individual specific-means.³² When centering, the value of zero represents an occupation in which routine and non-routine tasks are performed with roughly the same intensity.

Table 5 presents the results for the whole sample. There is no significant coefficient associated with outward FDI which suggests that workers with an offshorability score of zero experience no significant wage increase when their employer increases the number of foreign affiliates. However, we find a negative and significant coefficient associated with the offshorability index. This result suggests that FDI can have a negative effect on wages when the offshorability index becomes positive. FDI reduces wages by 0.30% when the offshorability score increases by one unit.

When we split the results into FDI in low-income countries and high-income countries, the interaction term turns out to be significant only for FDI in low-income countries. Outward FDI in low-income countries is more likely to correspond to offshoring, which is more damaging for manual-intensive workers. This result is consistent with evidence that workers with routine tasks experience larger wage cuts when their industry increases offshoring (Hummels et al., 2014).

6. Indirect effect of outward FDI on worker-level wage

Section 5 has identified a positive effect of outward FDI on workers' wages. However, the magnitude of the effect is very low. In section 6.1 we attempt to estimate whether outward FDI might play an indirect role on worker-level wages by impacting firm productivity (productivity effect of FDI). The productivity effect is high in the sample of managers. Section 6.2 attempts to estimate whether FDI influences rent-sharing and composition effect.

6.1. Productivity effect

There is an indirect effect of FDI through what is called a productivity effect. The mechanism of the productivity effect of FDI is the following. Outward FDI might increase firm profitability and productivity through an increase in output and a decrease in cost. In response, workers might benefit from this productivity effect by an increase in wages.

The coefficient from the baseline regression corresponds to the direct effect of outward FDI on wages when controlling for the productivity effect. One way of identifying the productivity effect of outward FDI is to drop controls for firm productivity in the regression and to compare the results with our baseline regression (Hummels et al., 2014). This productivity effect is measured by allowing time-varying firm-level variable (such as revenue and capital) to rise in response to an FDI shock.

When comparing Tables 3 and 6, we observe that the coefficients associated with FDI in the groups of occupations of blue-collar workers and intermediate occupations remain non-significant in both tables. On the contrary, the coefficient associated with the number of FDIs in the sample of managers increases when we drop controls for productivity (see Table 6). The coefficient associated with FDI goes from 0.077 in Table 3 to 0.101 in Table 6. Hence, about one third of the positive wage effects of FDI observed for managers is due to a productivity effect. This suggests that outward FDI positively affects productivity and it is possible that only managers are able to capture these productivity gains if there are information asymmetries in the wage bargaining process.

³² Balli and Sørensen (2013) show that centering in panel data should be subtracted to the interaction term by using individual specific-means and not the average across all observations.

Table 7
FDI and wage component of inequality.

	Skill-composition		Rent Sharing	
	(1) OLS	(2) FE	(3) OLS	(4) FE
FDI	0.006*** [0.001]	0.003 [0.004]	0.002*** [0.000]	0.008*** [0.002]
Observation	16,937	16,937	16,937	16,937
R-squared	0.017	0.013	0.001	0.026

Note: OLS denotes Ordinary Least Squares and FE stands for fixed effects. We add all other time-varying firms characteristics as described in previous tables. Our variable of interest *FDI* is measured by the number of foreign subsidiaries.

Compared to Denmark, the contribution of the productivity effect in France is very high (see [Hummels et al. \(2014\)](#) for comparison). One explanation for this result might be due to stronger union membership in France³³ According to [Kramarz \(2008\)](#) strong unions might increase the quasi-rent, the total pie shared between the workers and the firm, which allow them to capture a firm's productivity rent more easily.

6.2. Decomposing wages into skill-composition and rent-sharing effects

The productivity effect can work in different directions. On the one hand, workers can benefit from the productivity increase by capturing firm rent. On the other hand, the rise in productivity can allow firms to attract the best workers by spending more resources to screen and evaluate candidates. According to the results in section 3.2, the unobserved component of the positive discrimination of being employed in a multinational company accounts for a large share of the multinational wage premium. Hence, in order to disentangle these two effects, we follow the methodology described in section 4.3 to retrieve the unobserved firm and worker effect from the baseline regression.³⁴ We then analyze the role of outward FDI on these unobserved fixed effects.

The firm fixed-effect captures the ability of workers to take up firm rents (we label it RS, which stands for rent-sharing) and the workers fixed-effect captures the ability of the firm to attract the best workers (labeled SC for skill-composition).

[Table 7](#) analyzes the correlation between wages and FDI and offers some suggestive evidence on the association between skill composition and rent sharing and the multinational wage premium.

The OLS estimates are reported in columns (1) and (3). The firm fixed-effect is reported in column (2) and (4). The result of the OLS show that FDI is positively correlated with average firm and person-effect. However, when integrating firm fixed-effects, the coefficient associated with FDI when estimating skill-composition is no longer significant. FDI is significantly correlated with rent-sharing but is no longer significant when estimating skill-composition. This finding is very similar to [Frías et al. \(2012\)](#) and [Macis and Schivardi \(2016\)](#). This result indicates that the increase of outward FDI causes wages to be higher, and this effect is principally due to a greater ability of workers to capture firm rents, i.e. a rent sharing mechanism rather than a change in the firm's unobservable skill composition.

7. Conclusion

This article analyzes the effect of outward FDI on hourly wages within occupations, using panel data on French firms for the years 2002–2007. We use a rich French firm-level panel dataset with matched information on worker characteristics. We first analyze the evolution of the wage dispersion during the period 2002–2007. In line with recent literature, we observe that most of the variance of wage inequality took place within occupations. This wage dispersion is mainly due to firm heterogeneity and to a lesser extent to wage dispersion within firms. Our article focuses on the contribution of firm heterogeneity and more precisely on the role of outward FDI in explaining wage inequality within occupations.

We find evidence for a *multinational* wage premium within each skill groups, regardless of observable firm and individual characteristics. We isolate the impact of outward FDI on wage dispersion within occupations, using the framework developed by [AKM \(1999\)](#), in order to control for firm and person fixed effects and for the non-random matching process between firms and workers. The study reveals that outward FDI decreases the wage of workers whose tasks are more easily offshorable. The negative effect of outward FDI on offshorable tasks is consistent with the existence of substitutability between low-skilled workers performing offshorable tasks and workers in foreign affiliates.

In addition, outward FDI to low-income countries, which is a proxy for intra-firm offshoring, has a significant and positive impact on manager wages. However the data does not allow us to identify precisely the channels through which outward FDI acts on domestic wages, especially in the case of managers. First, outward FDI might push multinational firms to increase the range of worker skills as well as their span of control and/or workload. Individualized wage settings can be a good solution

³³ In 2002 the share of reported union membership was 20.4% in Denmark and 33% in France ([Visser, 2006](#)).

³⁴ We drop the variable on outward FDI from the baseline regression as it is our variable of interest in this section.

for creating incentives for workers to provide full effort in the decentralization process (Lemieux et al., 2009). Second, managers might prove to be more effective in bargaining over their employer's profits. They might consider themselves as important contributors to the success of foreign affiliates and might claim greater wage compensation compared to other workers in the firm. Finally, increased competition might push multinational firms to adopt new technologies. Following Nelson and Phelps (1966) view on human capital, skilled workers might adapt more quickly to changes in the organization of the firm and to the adoption of defensive technology. As these changes may require additional training and efforts, skilled-workers may be rewarded for it. In identifying these channel we highlight promising avenues for future research on the impact of FDI on wages.

In the last section, we identify the relative importance of skill-composition and rent sharing mechanisms to explain the effect of foreign direct investments on wages. The results indicate that the increase of outward foreign direct investment cause wages to be higher, and this effect is principally due to rent-sharing mechanisms.

A. Descriptive statistics

Table A.1

Education and occupation description.

label code	Education
0	No degree reported
1	Completed elementary school
2	Completed junior high-school
3	Basic professional degree
4	Professional high school degree
5	General high school degree
6	Professional college degree
7	University degree, engineering school, Grandes écoles
	CSP
3	Managers
4	Intermediate occupations
5	Employees
6	Blue-collar workers

Note: Education and occupations description for variance analysis as described in footnote.¹⁵

Table A.2

Descriptive statistics: Gross hourly wages by occupation and firm.

	Domestic	importers	exporters	importers and exporter	multinational with one subsidiary	multinational with 2–4 subsidiaries	multinational with more than 5
Managers							
Average hourly gross wage	27.708	29.403	26.995	31.533	30.285	31.846	32.526
standard deviations	[10.402]	[12.668]	[9.783]	[14.470]	[9.803]	[11.111]	[12.288]
observations	234	410	341	5031	751	1132	1728
Blue-collar workers							
Average hourly gross wage	12.889	13.056	12.537	13.319	13.831	13.924	14.575
standard deviations	[3.260]	[4.185]	[3.244]	[3.420]	[3.484]	[3.232]	[3.496]
observations	1700	2080	1651	21514	2571	3619	3005
Intermediate occupations							
Average hourly gross wage	17.417	18.059	16.854	18.384	18.547	18.808	19.612
standard deviations	[12.519]	[4.862]	[4.583]	[5.027]	[4.976]	[4.881]	[5.077]
observations	491	713	500	8862	1385	1850	2170
Administrative employee							
Average hourly gross wage	12.754	13.973	13.188	13.934	14.744	14.534	15.109
standard deviations	[3.083]	[4.478]	[3.193]	[3.364]	[3.663]	[3.702]	[3.833]
observations	150	189	187	1896	287	350	456

Source: LIFI survey, French annual census for manufacturing (EAE), French Déclaration annuelles des donnés sociales (Panel DADS-EDP); period: 2002–2007.

Robust standard error in brackets, ***p < 0.01, **p < 0.05, *p < 0.10.

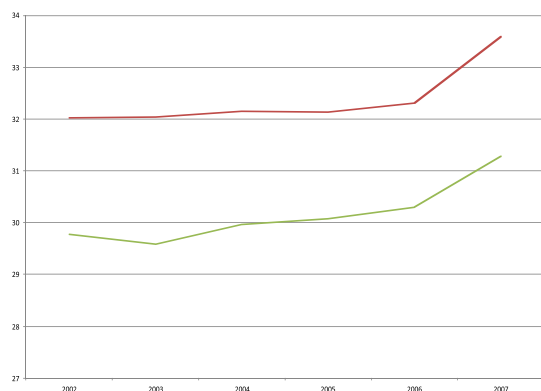
Table A.2 depicts the mean raw wage according to the firm's international status, within each group of occupations (managers, intermediate occupations, administrative employees, blue-collar workers). We observe that for each category, workers in multinational companies globally earn more than workers in all other types of firms: exporting, importing firms, domestic firms and those displaying only one form of internationalization (imports or exports). Average wages also appear to increase with the number of foreign affiliates. The mean wage gap between workers in domestic firms and workers in multinational firms with at least 5 foreign subsidiaries goes from 13% for intermediate occupations and blue-collar workers to 17% for managers and 18% for administrative employees.

Table A.3

Descriptive Statistics according to international status of firm.

	All			Domestic Firms			Multinational Firms		
	Obs	Mean	SD	Obs	Mean	SD	Obs	Mean	SD
Diploma:									
No diploma	114,439	0.134	0.341	83,481	0.144	0.351	30,958	0.109	0.313
Completed Elementary-School	114,439	0.061	0.238	83,481	0.061	0.241	30,958	0.056	0.231
Completed Junior High-school	114,439	0.085	0.281	83,481	0.089	0.286	30,958	0.075	0.264
Basic Professional degree (CAP)	114,439	0.229	0.421	83,481	0.236	0.425	30,958	0.212	0.409
Basic Professional degree (BEP)	114,439	0.121	0.326	83,481	0.124	0.329	30,958	0.115	0.319
Professional high-school degree	114,439	0.045	0.208	83,481	0.044	0.205	30,958	0.050	0.218
General high-school degree	114,439	0.108	0.311	83,481	0.108	0.31	30,958	0.109	0.312
Professional college degree	114,439	0.121	0.326	83,481	0.114	0.318	30,958	0.139	0.346
University degree	114,439	0.093	0.291	83,481	0.078	0.269	30,958	0.132	0.339
Sex:									
Female	129,110	0.292	0.454	94,407	0.293	0.455	34,703	0.289	0.453
Male	129,110	0.708	0.454	94,407	0.707	0.455	34,703	0.711	0.453
Number of Children	126,185	0.993	1.076	92,215	0.988	1.077	33,970	1.013	1.075
Marriage	127,385	0.479	0.499	92,215	0.471	0.499	34,254	0.504	0.499
Age	129,110	39.82	9.746	94,407	39.493	9.715	34,703	40.707	9.774
Value-added per worker	128,811	71.381	264.79	94,110	68.221	286.533	34,703	79.951	196.661
Capital per worker	128,811	20.712	55.634	94,110	14.541	49.461	34,703	37.447	66.872
Revenue per worker	128,811	247.687	969.539	94,110	231.129	1085.933	34,701	292.595	537.056
Exports in euros	129,110	212,701.7	633,469.6	94,407	132,057.2	565,857	34,703	432,089.2	745,702.7
FDI	129,110	2.274	9.319	94,407	0	0	34,703	8.460	16.456
Subsidiaries in France	129,110	1.984	5.708	94,407	0.633	2.137	34,703	5.656	9.503

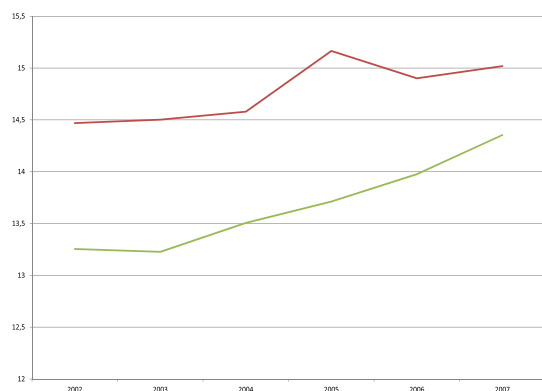
Source: LIFI survey, French annual census for manufacturing (EAE), French Déclaration annuelles des données sociales (Panel DADS-EDP); period: 2002–2007.



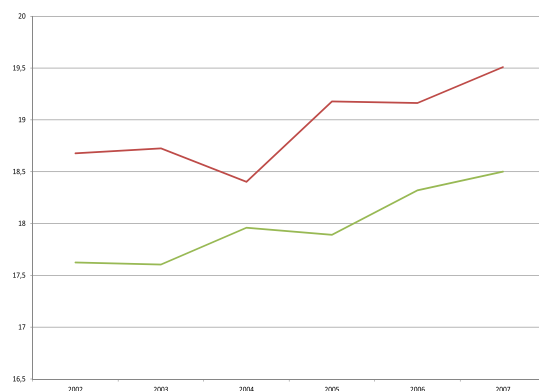
(a) Managers



(b) Blue collar workers



(c) Employees



(d) Intermediate Occupations

Source: LIFI survey, French annual census for manufacturing (EAE), French Déclaration annuelles des données sociales (Panel DADS-EDP); period: 2002-2007. Statistics made on balanced sample, excluding energy sector.

Note: The red curves report the average wage for workers employed in multinational firms, the green curves report the average wage for workers employed in domestic firms.

Fig. A.1 Evolution of wage premium by occupations between multinational- and domestic-workers.

Table A.4
Descriptive Statistics by sector.

		Managers	Intermediate Occupations	Employee	Blue-collar Workers
Leather, clothing	Mean hourly wage	29.773	15.941	11.320	10.381
	Standard error	[12.450]	[6.829]	[3.827]	[2.714]
	Share of (in %)	7.120%	17.688%	18.953%	55.769%
Publishing, printing and reproduction	Mean hourly wage	28.225	17.529	13.044	14.322
	Standard error	[54.678]	[6.301]	[3.860]	[5.618]
	Share of (in %)	30.491%	16.341%	13.616%	39.212%
Pharmaceuticals, perfumery and personal care	Mean hourly wage	35.943	20.468	14.491	13.637
	Standard error	[18.722]	[7.149]	[4.734]	[4.340]
	Share of (in %)	21.929%	40.257%	6.505%	31.178%
Home equipment	Mean hourly wage	29.791	16.809	12.123	11.609
	Standard error	[12.282]	[5.160]	[3.181]	[3.138]
	Share of (in %)	12.098%	19.929%	8.602%	59.073%
Automobile industry	Mean hourly wage	30.062	17.957	13.914	13.337
	Standard error	[13.191]	[6.645]	[4.563]	[3.687]
	Share of (in %)	10.580%	21.185%	3.639%	64.497%
Shipbuilding, aircraft and rail construction	Mean hourly wage	30.615	18.718	16.336	14.384
	Standard error	[11.705]	[5.129]	[4.864]	[4.963]
	Share of (in %)	2.484%	24.599%	5.994%	44.474%
Machinery industry	Mean hourly wage	29.151	17.152	12.596	12.867
	Standard error	[10.698]	[5.313]	[3.600]	[11.989]
	Share of (in %)	13.715%	25.150%	6.707%	53.963%
Electrical-equipment	Mean hourly wage	30.541	17.357	13.376	12.045
	Standard error	[12.510]	[5.462]	[4.263]	[3.627]
	Share of (in %)	36.364%	26.847%	6.184%	3.034%
Mineral product	Mean hourly wage	31.307	17.858	12.551	13.088
	Standard error	[13.667]	[5.063]	[3.706]	[3.832]
	Share of (in %)	10.100%	2.046%	7.738%	61.426%
Textile	Mean hourly wage	29.044	16.063	12.286	11.052
	Standard error	[11.771]	[5.375]	[3.248]	[2.749]
	Share of (in %)	6.996%	16.340%	8.626%	67.535%
Wood and paper product	Mean hourly wage	31.036	18.829	12.773	12.880
	Standard error	[12.300]	[9.501]	[3.495]	[4.445]
	Share of (in %)	7.423%	15.640%	6.309%	70.037%
Chemicals, rubber, and plastics	Mean hourly wage	33.628	18.884	13.486	13.014
	Standard error	[18.983]	[37.423]	[4.238]	[4.246]
	Share of (in %)	11.915%	25.049%	6.122%	56.618%
Non ferrous metals metallurgical transformation	Mean hourly wage	28.980	17.545	13.072	12.710
	Standard error	[12.248]	[5.278]	[3.755]	[3.645]
	Share of (in %)	7.673%	18.828%	5.857%	67.174%
Electronic components	Mean hourly wage	29.810	17.392	12.400	12.575
	Standard error	[15.462]	[5.497]	[3.892]	[3.651]
	Share of (in %)	20.089%	24.915%	4.879%	50.010%

Source: LIFI survey, French annual census for manufacturing (EAE), French Déclaration annuelles des données sociales (Panel DADS-EDP); period: 2002–2007.

B. Methodological tests

Table B.5
Exogeneity test of FDI .

	All sample	Managers	Blue-collar workers	Intermediate occupations
F-test: First stage	F = 28.58 p = 0.000	F = 13.74 p = 0.000	F = 11.56 p = 0.000	F = 21.40 p = 0.000
Kleibergen-Paap rk LM- stat of underidentification	$Chi^2 = 59.051$ p = 0.000	$Chi^2 = 25.678$ p = 0.000	$Chi^2 = 26.051$ p = 0.000	$Chi^2 = 20.084$ p = 0.000
C-test of Endogeneity	$Chi^2 = 0.239$ p = 0.6247	$Chi^2 = 1.687$ p = 0.194	$Chi^2 = 0.721$ p = 0.3958	$Chi^2 = 1.470$ p = 0.2254

Source: LIFI survey, French annual census for manufacturing (EAE), French Déclaration annuelles des données sociales (Panel DADS-EDP); period: 2002–2007. Robust standard error in brackets, ***p < 0.01, **p < 0.05, *p < 0.10. Excluded instruments FDI_{-1} , FDI_{-2} .

Table B.6

Person and firm effect model and match effect model.

	All		Managers		Blue-collar workers		Intermediate occupations	
	Match	Person-firm	Match	Person-firm	Match	Person-firm	Match	Person-firm
Number of FDI abroad	0.030** [0.012]	0.029** [0.012]	0.075*** [0.023]	0.077*** [0.023]	0.015 [0.027]	0.013 [0.027]	0.008 [0.016]	0.008 [0.016]
Revenue	0.013*** [0.006]	0.012*** [0.004]	0.001 [0.012]	−0.000 [0.013]	0.024*** [0.007]	0.024*** [0.007]	0.017*** [0.006]	0.018*** [0.006]
Capital	0.011* [0.006]	0.012* [0.006]	−0.005 [0.014]	−0.005 [0.014]	0.018 [0.012]	0.018 [0.012]	0.009 [0.009]	0.009 [0.009]
TFP	0.000 [0.000]	0.006 [0.006]	−0.000 [0.000]	−0.009 [0.016]	0.011 [0.010]	0.012 [0.009]	−0.000 [0.000]	−0.000 [0.000]
Imports of II	−0.000 [0.000]	−0.000 [0.000]	−0.000 [0.000]	−0.000 [0.000]	−0.000 [0.000]	−0.000 [0.000]	−0.001 [0.001]	−0.001 [0.001]
Imports of FG	0.000 [0.000]	0.000 [0.000]	0.000 [0.001]	0.000 [0.001]	−0.000 [0.001]	−0.000 [0.001]	0.001*** [0.000]	0.001*** [0.000]
Exports	0.027*** [0.005]	0.027*** [0.005]	−0.004 [0.014]	0.009 [0.013]	0.047*** [0.009]	0.044*** [0.009]	0.015** [0.007]	0.012* [0.007]
Observations	48,234		9144		23,867		15,223	
R-squared	0.103		0.120		0.076		0.131	
Number of person-firms	11,134		2318		5961		4123	

Source: LIFI survey, French annual census for manufacturing (EAE), French Déclaration annuelles des données sociales (Panel DADS-EDP); period: 2002–2007.

Robust standard error in brackets, ***p < 0.01, **p < 0.05, *p < 0.10.

C. Task measures

We build a routinization index derived from the French survey on working conditions, produced by the French Direction de l'Animation de la Recherche, des Etudes et des Statistiques (DARES) for the year 2005. The inquiry is carried out every 7 years on a sample of 19,000 workers.

We build the index from 9 questions on job characteristics:

Do you directly interact with a public? (always = 1; often = 2; sometimes = 3; never = 4)

Does your job involve the automatic movement of a machine? (No = 1; Yes = 2)

Does your job involve the automatic movement of a product? (No = 1; Yes = 2)

Are you an assembly-line production worker? (No = 1; Yes = 2)

Does your job consists in repeating a series of gestures or operations? (No = 1; Yes = 2)

Does your job involve monotonous tasks? (Never = 1; sometimes = 2; often = 3; always = 4)

Does your job involve complex tasks? (Always = 1; often = 2; sometimes = 3; never = 4)

Does your job require you to read documents? (Most of the time = 1; half of the time = 2; one quarter of the time = 3; less than one quarter of the time = 4; never = 5)

Does your job require you to write documents? (Most of the time = 1; half of the time = 2; one quarter of the time = 3; less than one quarter of the time = 4; never = 5)



Note: Average routinization index in eight 2-digit occupations: managers, engineers, technicians, administrative, foremen, secretary, skilled blue-collar workers, unskilled blue-collar workers. Source: French survey on working conditions, year 2005, author's calculation.

Fig. C.2 Task index by occupations with the French classification.

The questions selected in the French survey offer a clear picture of routinization. Managers and Engineers have the lowest index of routinization whereas skilled and unskilled blue-collar workers have the highest index.

The French index has the advantage of being built on the French PCS-ESE classification but has the disadvantage of relying on a small number of tasks related to the working conditions of the employee.

D. Additional results

D.1. Person-firm effect model

Table D.7
Robustness test: Number of countries deserved by Foreign Direct Investment.

	All	Managers	Blue-collar workers	Intermediate Occupations
Number of countries deserved	0.053** [0.022]	0.135*** [0.043]	0.048 [0.046]	0.013 [0.029]
Revenue	0.001** [0.001]	0.001 [0.001]	0.002* [0.001]	0.002*** [0.001]
Capital	0.001** [0.001]	−0.000 [0.002]	0.003** [0.001]	0.001 [0.001]
TFP	0.000* [0.000]	−0.000 [0.000]	0.000** [0.000]	−0.000 [0.000]
Imports of II	−0.000 [0.000]	−0.000 [0.000]	−0.000 [0.000]	−0.001 [0.001]
Imports of FG	0.000 [0.000]	0.000 [0.001]	−0.000 [0.001]	0.001*** [0.000]
Exports	0.028*** [0.005]	−0.004 [0.014]	0.047*** [0.009]	0.015** [0.007]
Constant	3.774*** [0.037]	4.399*** [0.106]	3.179*** [0.045]	3.970*** [0.066]
Observations	48,234	9144	23,867	15,223
R-squared	0.106	0.120	0.076	0.131
Log Likelihood	55181.374	9223.718	25717.089	18778.624

Source: LIFI survey, French annual census for manufacturing (EAE), French Déclaration annuelles des données sociales (Panel DADS-EDP); period: 2002–2007. Note: The regression includes individual-level controls such as number of children, marriage, computer use and age-squared. The full Table is available in the online appendix in the author's web page. Robust standard error in brackets, ***p < 0.01, **p < 0.05, *p < 0.10.

Table D.8

Robustness test: Inclusion of group nationality.

	All	Managers	Blue-collar workers	Intermediate Occupations
Number of FDI abroad	0.031** [0.012]	0.074*** [0.023]	0.020 [0.027]	0.008 [0.016]
Nationality	−0.003 [0.003]	0.004 [0.007]	−0.008* [0.004]	−0.001 [0.004]
Revenue	0.001** [0.001]	0.001 [0.001]	0.002* [0.001]	0.002*** [0.001]
Capital	0.001* [0.001]	−0.000 [0.002]	0.003** [0.001]	0.001 [0.001]
TFP	0.000 [0.000]	−0.000 [0.000]	0.000** [0.000]	−0.000 [0.000]
Imports of II	−0.000 [0.000]	−0.000 [0.000]	−0.000 [0.000]	−0.001 [0.001]
Imports of FG	0.000 [0.000]	0.000 [0.001]	−0.000 [0.001]	0.001*** [0.000]
Exports	0.026*** [0.005]	−0.004 [0.014]	0.046*** [0.009]	0.015** [0.007]
Constant	3.776*** [0.038]	4.399*** [0.106]	3.179*** [0.045]	3.971*** [0.066]
Observations	43,521	7494	21,858	13,150
R-squared	0.106	0.121	0.068	0.130
Log Likelihood	46528.915	7601.932	23569.178	16393.762

Source: LIFI survey, French annual census for manufacturing (EAE), French Déclaration annuelles des données sociales (Panel DADS-EDP); period: 2002–2007.

Note: The regression includes individual-level controls such as number of children, marriage, computer use and age-squared. The full Table is available in the online appendix on the author's web page. Robust standard error in brackets, ***p < 0.01, **p < 0.5, *p < 0.10.

Table D.9

Robustness test: Sample of firms having less than 5 subsidiaries.

	All	Managers	Blue-collar workers	Intermediate Occupations
Number of FDI abroad	−0.074 [0.178]	−0.453 [0.382]	−0.130 [0.216]	0.246 [0.206]
Revenue	0.002*** [0.001]	0.001 [0.002]	0.001 [0.001]	0.000 [0.001]
Capital	0.002** [0.001]	0.000 [0.002]	0.004*** [0.001]	0.001 [0.001]
TFP	0.000 [0.000]	−0.000 [0.000]	0.000** [0.000]	0.000 [0.000]
Imports of II	−0.000 [0.000]	−0.000 [0.000]	−0.000 [0.000]	−0.001 [0.001]
Imports of FG	0.001 [0.000]	0.000 [0.001]	−0.000 [0.001]	0.001*** [0.000]
Exports	0.020*** [0.007]	0.001 [0.016]	0.033*** [0.010]	0.029*** [0.009]
Constant	3.708*** [0.042]	4.462*** [0.119]	3.165*** [0.048]	3.885*** [0.071]
Observations	40,495	7494	21,858	13,150
R-squared	0.102	0.121	0.068	0.130
Log Likelihood	43284.391	7601.337	23567.741	16393.349

Source: LIFI survey, French annual census for manufacturing (EAE), French Déclaration annuelles des données sociales (Panel DADS-EDP); period: 2002–2007.

Note: The regression includes individual-level controls such as number of children, marriage, computer use and age-squared. The full Table is available in the online appendix on the author's web page. Robust standard error in brackets, ***p < 0.01, **p < 0.5, *p < 0.10.

Table D.10

Robustness test: Extensive versus Intensive margin.

	All		Managers		Blue-collar workers		Intermediate Occupations	
	Extensive	Intensive	Extensive	Intensive	Extensive	Intensive	Extensive	Intensive
Number of FDI abroad	0.005*	0.028**	0.015**	0.071***	−0.001	0.014	0.007*	0.007
	[0.003]	[0.012]	[0.007]	[0.025]	[0.004]	[0.025]	[0.004]	[0.015]
Revenue	0.001**	0.001	0.001	−0.001	0.002*	0.001	0.002**	0.002**
	[0.001]	[0.001]	[0.001]	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]
Capital	0.002**	0.001	−0.000	−0.001	0.003**	0.000	0.001	0.002
	[0.001]	[0.001]	[0.002]	[0.002]	[0.001]	[0.002]	[0.001]	[0.001]
TFP	0.000	−0.000	−0.000	−0.000	0.000**	−0.000	−0.000	−0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Imports of II	−0.000	−0.002	−0.000	−0.002	−0.000	−0.001	−0.000	−0.001
	[0.000]	[0.001]	[0.000]	[0.003]	[0.000]	[0.003]	[0.001]	[0.002]
Imports of FG	0.000	0.001	0.000	0.001	−0.000	−0.000	0.001***	0.001**
	[0.000]	[0.000]	[0.001]	[0.002]	[0.001]	[0.001]	[0.000]	[0.000]
Exports	0.028***	0.035***	−0.001	0.014	0.046***	0.083***	0.017**	0.006
	[0.005]	[0.008]	[0.014]	[0.026]	[0.009]	[0.016]	[0.007]	[0.010]
Constant	3.774***	3.662***	4.398***	4.302***	3.180***	3.138***	3.966***	3.862***
	[0.038]	[0.056]	[0.106]	[0.218]	[0.045]	[0.087]	[0.066]	[0.090]
Observations	48,234	14,225	9144	3457	23,867	5681	15,223	5087
R-squared	0.103	0.133	0.119	0.105	0.076	0.133	0.131	0.161
Log Likelihood	51321.281	15412.108	9220.554	3186.371	25715.830	6550.163	18775.691	6496.885

Source: LIFI survey, French annual census for manufacturing (EAE), French Déclaration annuelles des données sociales (Panel DADS-EDP); period: 2002–2007.

Note: The regression includes individual-level controls such as number of children, marriage, computer use and age-squared. The full Table is available in the online appendix on the author's web page. Robust standard error in brackets, ***p < 0.01, **p < 0.5, *p < 0.10.

D.2. Regression based on industries

We use the OECD classification to assign industries either to the low- or to the medium/high-tech sector.³⁵ We run separate estimations in the sample of firms belonging to the high tech and low-tech industries in order to test whether the offshoring activities had a stronger impact on wage inequalities in high tech sectors compared to low tech sectors.

Results are reported in the following Table.

Table D.11

Spell fixed effects by low-tech and high-tech industries.

	All		Managers		Blue-collar workers		Intermediate Occupations	
	low-tech	high-tech	low-tech	high-tech	low-tech	high-tech	low-tech	high-tech
Number of FDI abroad	0.023*	0.090	0.066***	0.573***	0.012	−0.112	0.002	0.195*
	[0.012]	[0.075]	[0.023]	[0.195]	[0.026]	[0.108]	[0.017]	[0.114]
Revenue	−0.001**	0.008***	0.001	0.004	−0.005***	0.010***	0.000	0.007***
	[0.001]	[0.002]	[0.002]	[0.005]	[0.001]	[0.003]	[0.001]	[0.002]
Capital	0.002***	−0.026***	−0.000	−0.047***	0.005***	−0.026***	0.002*	−0.023***
	[0.001]	[0.004]	[0.002]	[0.012]	[0.002]	[0.007]	[0.001]	[0.005]
TFP	0.000***	−0.000	−0.000	−0.000	0.000***	−0.000	0.000	−0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Imports of FG	0.001**	−0.000	−0.001	−0.002	0.000	−0.000	0.002***	−0.000
	[0.000]	[0.001]	[0.002]	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]
Imports of II	−0.000	−0.000	0.002	−0.000	−0.000	−0.000	−0.002	0.000
	[0.000]	[0.000]	[0.002]	[0.000]	[0.000]	[0.001]	[0.001]	[0.001]
Exports	0.038***	0.006	0.010	−0.037	0.080***	0.041*	0.021**	−0.002
	[0.007]	[0.013]	[0.016]	[0.038]	[0.014]	[0.024]	[0.010]	[0.015]
Constant	3.572***	3.476***	4.442***	4.080***	3.149***	3.272***	3.589***	3.763***
	[0.043]	[0.051]	[0.124]	[0.310]	[0.068]	[0.070]	[0.077]	[0.092]
Observations	23,702	19,771	5886	2693	9790	11,309	8026	5769
R-squared	0.120	0.090	0.123	0.121	0.093	0.070	0.135	0.136
Log Likelihood	26240.959	20060.222	5956.029	2654.020	11442.383	11576.548	9772.545	7189.584

Source: LIFI survey, French annual census for manufacturing (EAE), French Déclaration annuelles des données sociales (Panel DADS-EDP); period: 2002–2007.

Note: The regression includes individual-level controls such as number of children, marriage, computer use and age-squared. The full Table is available in the online appendix on the author's web page. Robust standard error in brackets, ***p < 0.01, **p < 0.5, *p < 0.10.

³⁵ The classification of low-tech and high-tech industries are based on the NACE classifications. Chemicals; pharmaceuticals; machines and equipment; computers, electronic and optical products and transports are classified in the high-tech industries, whereas the others are classified in the low-tech industries.

Appendix E. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.inteco.2018.12.001>.

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