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Globalization and imperfect labor market sorting

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ABSTRACT

This paper focuses on the ability of the labor market to efficiently match heterogeneous workers to jobs within a given industry and the role that globalization plays in that process. Using matched worker–firm data from Sweden, we find strong evidence that openness improves the matching between workers and firms in industries with greater comparative advantage. This suggests that there may be significant gains from globalization that have not been identified in the past — globalization may improve the efficiency of the matching process in the labor market. These results remain unchanged after adding controls for technical change at the industry level or measures of domestic anti-competitive regulations and product market competition. Our results are also robust to alternative measures of the degree of matching, openness, and the trade status of an industry.

1. Introduction

This paper is an empirical exploration of how well the labor market matches good workers with good firms within a given industry, focusing in particular on the degree to which increased globalization might impact that process. Our work is motivated by earlier research that has attempted to empirically measure the correlation between firm and worker quality combined with relatively recent theoretical work suggesting that globalization can influence this correlation differentially based on an industry's degree of comparative advantage.[1]

The idea of matching heterogeneous agents dates back to the classic paper by Becker (1973) on the marriage market.[2] Becker introduced the issue by pointing out that men differ in a variety of attributes including physical capital, intelligence, education, wealth and physical characteristics and it is unclear how these men ought to be matched with similarly heterogeneous women. Becker argued that under reasonable assumptions about the household production function, positive assortative matching — the matching of men and women with similar attributes — would be optimal. Similar issues apply to the labor market where even in narrowly defined industries firms differ in the technologies they use, the skill-mix of their workforces, and the wages that they pay (Doms et al., 1997) and workers differ in education, physical attributes and ability. A large literature has developed in search theory devoted to finding conditions under which positive assortative matching is optimal in labor markets with two-sided heterogeneity

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[1] See for example Abowd et al. (1999), Goux and Maurin (1999), Gruetter and Lalive (2004), Barth and Dale-Olsen (2003) for the empirical motivation; and Davidson et al. (2008) and Helpman et al. (2010) for the theoretical motivation.

[2] Closely related to the matching problem described by Becker is the "assignment problem" associated with early models by Tinbergen (1951) and Roy (1951) (see Sattinger, 1993 for a survey). Becker is concerned with one-to-one matching — matching males and females in the marriage market or a single worker with a firm in the labor market. Assignment models focus on firms that hire multiple workers and then assign those workers to a variety of tasks.

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and conditions under which the market outcome yields the optimal pattern of sorting (e.g., Shimer and Smith, 2000; Legros and Newman, 2002, 2007). The pioneering work of Abowd et al. (1999) offered a methodology that could be used to test for positive assortative matching and a good deal of research in labor economics that followed focused on whether labor markets are characterized by this type of matching. Most of this work has produced surprising results that suggest that a great deal of matching may be inefficient.[3]

This is an important issue in international trade, where the implications of firm and worker heterogeneity have been major topics of research over the past two decades.[4] In particular, the results derived in Davidson et al. (2008) as well as in Helpman et al. (2010) suggest that increased globalization could have an effect on the matching of firms and workers. Specifically, Davidson et al.'s (2008) analysis suggests that increased openness to international trade affects the correlation between worker and firm productivity: increasing this correlation in "comparative-advantage" industries; but weakening it in "comparative-disadvantage" industries. Similarly, Helpman et al. (2010) show that in their setting greater openness strengthens the correlation between firm productivity and average worker ability; a result that is consistent with greater openness resulting in an increase in positive assortative matching.

These theoretical results, discussed in more detail below, provide the motivation for undertaking the empirical analysis in this paper where we ask if there is any empirical evidence whatsoever linking globalization to firm-worker matching. This is the heart of the matter. Has the quality of worker–firm matches changed over time? If so, can any of that change be attributed to changes in the degree to which an economy is engaged globally? If globalization is found to have an effect, is that effect industry-specific, depending on whether the industry is export-oriented (a comparative-advantage industry) or import-competing (a comparative-disadvantage industry)?

The data requirements to carry out this type of analysis are demanding. We need extensive information about workers, firms, and their employment relationships over time. We are able to meet these demands by combining data from Statistics Sweden's annual salary survey with a variety of other data registers to obtain a comprehensive view of Swedish industries, workers, and firms. This matched employer–employee data spans a decade, so we are able to track workers as they either remain employed with the same firm throughout the sample, transit to new firms, or exit the labor force. The data set is extensive, including roughly 50% of the workforce and all firms in Sweden with more than 20 employees, and rich in details concerning worker and firm characteristics. The data set is also characterized by considerable worker mobility, allowing us to avoid the issue of "limited mobility bias" that has been associated with previous empirical studies of assortative matching using linked employee–employer data (see Andrews et al., 2008).

Our empirical approach begins with the construction of a measure of the degree of matching in disaggregated industries using both observed attributes and unobserved fixed effects of workers and firms. The unobserved worker and firm effects are estimated using the approach taken by Abowd et al. (1999) and the literature that has followed. Once constructed, we then explore the degree to which "openness" can explain variation in this variable between industries and over time. Our preferred measure of openness is tariffs. The main advantage of using tariffs is that they can be considered as exogenous after 1995 when Sweden joined the European Union, since it is unlikely that a small country like Sweden can have a substantial impact on the level of tariffs set by the EU. In addition, foreign tariffs are not affected by conditions in Swedish industries. However, "openness" or "globalization" has many dimensions. We therefore test the robustness of our results by constructing alternative measures of openness.

Focusing here on our preferred measure, reducing foreign tariffs imposed on Swedish exports has the largest effect on Swedish exporters, therefore such tariff reductions ought to increase the chances that good workers match with good firms. In contrast, a reduction in Swedish tariffs imposed on foreign imports largely impacts Swedish importers. The intuition from Davidson et al. (2008) suggests that these changes might make it more difficult for good workers to match with good firms.[5]

Fig. 1 gives us a first glance of the Swedish data. Each point in the figure represents one of 73 three-digit Swedish industries. There are 33 comparative-advantage industries each represented by a closed circle and 40 comparative-disadvantage industries each represented by an x.[6] The vertical axis represents the 10-year difference between 1995 and 2005 in the degree of matching within each industry, where a positive difference represents an increase in the strength of correlation between worker and firm quality.[7] The horizontal axis represents the 10-year change in the industry-specific foreign tariff rate. In calculating these differences, we treat reductions in foreign tariffs applied to Swedish goods as positive numbers, so that an increase can be thought of as reduced trade barriers or greater openness.

The dotted and solid lines represent the OLS fitted regression of the change in matching against the change in tariffs without controlling for any other factors. The slope of the dotted line is flat and not statistically different from zero. As a first pass, greater openness had no impact on the degree of matching in Sweden's comparative-disadvantage industries. In contrast, the estimated slope of the solid line is 0.08 with a standard error of 0.05, giving a p-value of 0.135. Without any controls, it appears that there was a positive correlation between greater openness and the quality of matching in Sweden's comparative-advantage industries.

In the analysis to follow, we dig deeper into the data and pool all industries and years to exploit the full information contained in the data set. Controlling for industry and year fixed effects, we identify the effect of openness on the degree of matching by exploiting the within-industry and over-time variation in the measures of openness and the degree of matching. In addition, we investigate the possibility that the effect of openness could be systematically related to the trade status of an industry. Recognizing that there may be a myriad of influences at work, we attempt to isolate the effect of openness by controlling for other industry-level time-varying factors that may affect the degree of matching. For example, both Acemoglu (1999) and Albrecht and Vroman (2002) argue that skill-biased technical change increases the degree of positive assortative matching. Product market competition may also affect the profitability of firms and the degree of matching between firms and workers. Thus, in our investigation of the relationship between openness and assortative matching, we add industry-level controls for those factors.

[3] From an anecdotal perspective, most readers of this article probably know many academic economists who are "under placed", including everyone reading this article.

[4] A number of important papers examine how labor market sorting affects trade issues including Grossman and Maggi (2000), Grossman (2004), Yeaple (2005), Antràs et al. (2006), Kremer and Maskin (2006), Ohnsorge and Trefler (2007), Costinot (2009), and Costinot and Vogel (2010), among others.

[5] As will be described in Section 2, Davidson and Matusz (2012) refine the Davidson et al. (2008) by allowing for a continuum of firm productivities operating in a monopolistically-competitive market. The refined model suggests that intensified import competition may have an ambiguous impact on matching, while increased access to export markets remains to have an unambiguously positive impact on assortative matching.

[6] Comparative-advantage (comparative-disadvantage) industries are defined as having positive (negative) net exports in the initial year of the data (1995). Our sample has 88 three-digit SNI (Swedish Industrial Classification) industries. However, 15 of them have missing information on tariffs for 1995. Also note that in the following empirical analysis, we mainly use a continuous measure of trade status of an industry, which is defined as the value of net exports as a share of total trade in 1995 for that industry. See Section 3.4 for more details.

[7] In the plot, the degree of matching is measured by the correlation coefficient between worker and firm total effects (including both observed and unobserved attributes). See Section 3.2 for details about this measure.

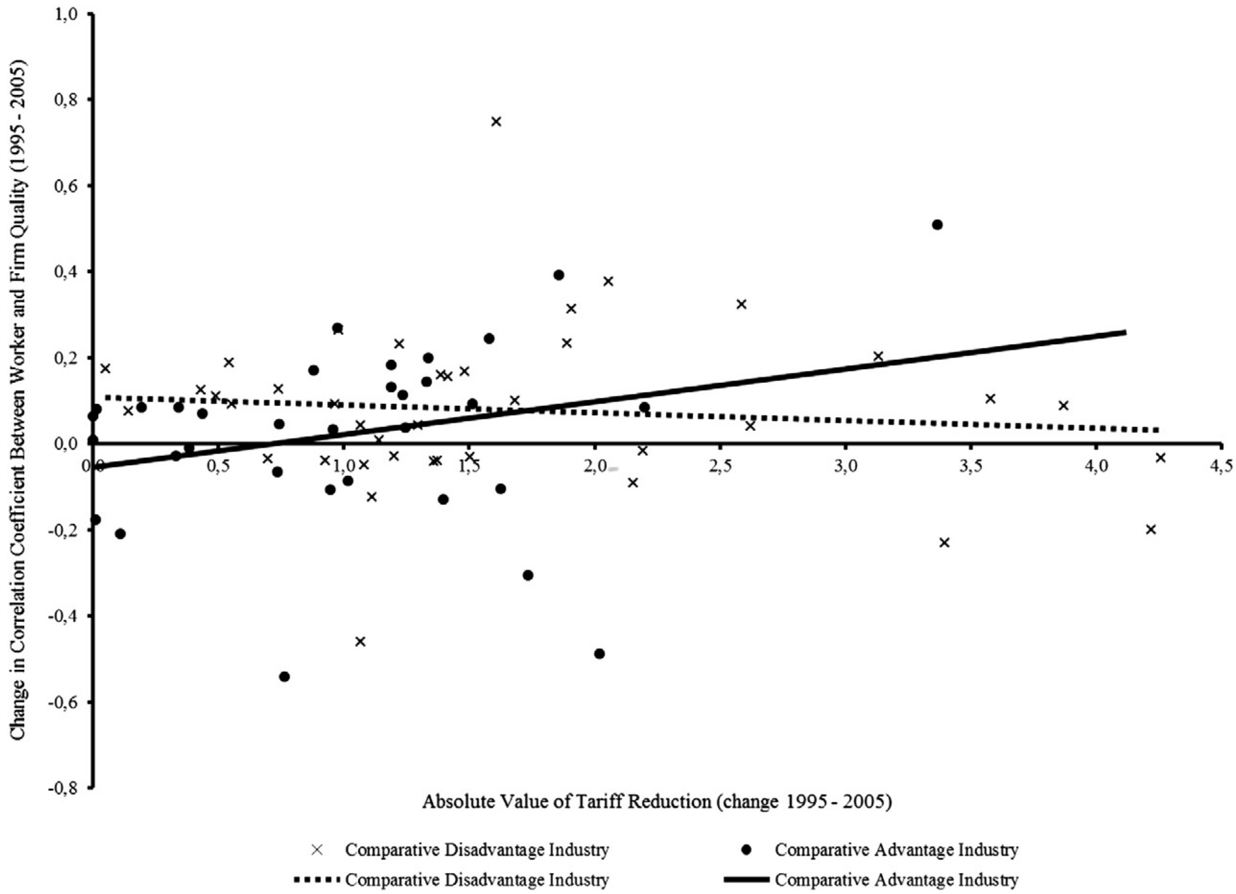

Fig. 1. Changes in industry-specific foreign tariff rates and changes in the degree of matching within industries.

We find strong evidence that openness improves the matching between workers and firms in industries with greater comparative advantage. Our baseline results, presented in Section 4, imply that lower tariffs result in better worker–firm matching in more than 80% of the industries in our sample and the effect is substantial. For the 20 industries with the largest comparative advantage, matching improves on average by 1.15 standard deviations when tariffs fall by 1 standard deviation.[8] Improved matching leads to more output to the extent that worker and firm productivity are complements, but the exact magnitude of this effect cannot be quantified without detailed information about the production technology and the joint distribution of worker and firm productivity.[9] However, our results still suggest that there may be potential gains from globalization that have not been identified in the past — globalization may improve the efficiency of matching in the labor market. Our main results remain unchanged after adding controls for technical change at the industry level or measures of domestic anti-competitive regulations and product market competition. Our results are also robust to alternative measures of the degree of matching, openness, and the trade status of an industry.

In the next section, we provide brief descriptions of some mechanisms that could connect increased globalization with stronger assortative matching. In Section 3 we describe the empirical approach that we take and discuss the data set and measurement issues. Our baseline empirical results and robustness checks are presented in Section 4. We realize that one potential weakness of our analysis is that our measure of the degree of matching is constructed using estimates of an AKM-type wage regression (Abowd et al., 1999), an approach that has been criticized recently on several grounds. Thus, it is worth emphasizing that our discussion in Sections 3 and 4 highlights the main criticisms of this approach and that many of our robustness checks are aimed at dealing with the issues previous researchers have raised about the AKM methodology.[10]

2. Theoretical foundations

Davidson et al. (2008) and Helpman et al. (2010) both develop theoretical models consistent with the result that increased access to export markets results in increased intra-industry correlation between worker and firm productivity.[11] Both models assume heterogeneous firms, and both assume that the production function is super modular in firm and worker productivity, so that positive assortative matching is optimal.[12] Both also assume that search frictions make it impossible for firms to always employ their ideal workforce. The two models differ in their assumptions about heterogeneity in the labor market. For DMS, there are two types of workers with high-ability workers being more productive than their low-ability counterparts. Firms differ by their endogenously-chosen technology. A firm can select either a basic or a

[8] The 20 industries with the largest comparative advantage are listed in Table A8. See footnote 21 for an example of how to calculate the impact on the degree of matching due to a tariff cut.

[9] Let ϕ and θ represent worker and firm productivity, and let ρ represent their correlation. Define the joint density $f(\phi, \theta; \rho)$ and the production function $q = Q(\phi, \theta)$. Then expected output depends on the correlation between worker and firm effects: $E(q; \rho) = \iint f(\phi, \theta; \rho)Q(\phi, \theta)d\phi d\theta$.

[10] The three main criticisms that we address are "limited mobility bias" (see Section 3.2), the exclusion of match effects (see Section 4.4) and the reliability of the estimate of firm quality (see Section 4.10).

[11] Hereafter we refer to Davidson et al. as DMS, and Helpman et al. as HIR.

[12] DMS introduce firm heterogeneity in the same manner as Yeaple (2005) in that firms choose from a menu of production technologies when entering the industry. Each choice yields the same expected profit in equilibrium, therefore ex ante homogeneous firms make different choices, resulting in ex post heterogeneity.

modern technology to produce output. While the modern technology (characterized as "high-tech") is more productive than the basic technology, it can only be operated by a high-ability worker, whereas the basic technology (characterized as "low-tech") can be operated by either worker type. In equilibrium, both types of firms co-exist with low-tech firms paying lower wages and employing a less productive workforce. In contrast, firm heterogeneity in HIR is introduced as in Melitz (2003) and workers are ex-ante homogeneous, but have match-specific heterogeneity. In addition, because there are costs to a bad match, HIR assume that firms invest real resources to screen out the least productive workers. While the DMS model is developed in the context of a perfectly-competitive industry, both models share the feature that only the most productive firms are able to overcome trade costs to enter the export market, as in Melitz (2003). Exporters are then larger and have higher productivity than non-exporters. Because of the complementarities with worker productivity, this means that high-ability workers are more valuable to exporting firms than they are to non-exporters. A change in the environment that permits greater access to export markets has four effects. First, more firms are able to start exporting. Second, those that had originally been exporters become larger, earning greater revenues. The increased revenue increases the ability of the most productive firms to compete for the best workers. Third, in DMS the greater access to world markets triggers new entry by firms adopting the modern technology, while in HIR firms at the low-end of the productivity scale are squeezed out of the market due to the increased market presence of the most productive firms. Fourth, in HIR exporters have an incentive to screen more intensively. With random matching of unemployed workers with firms, all four of these effects increase the likelihood that high-ability workers will be matched with highly-productive firms, therefore increasing the degree of assortative matching. The first two effects, combined with intensified screening, suggest that the degree of matching would increase among the existing set of firms, while the third reason suggests that assortative matching would increase due to entry of new highly-productive firms combined with a truncation of firm productivity.

Davidson and Matusz (2012) refine the DMS model to allow for a continuum of firm productivities operating in a monopolistically-competitive market, a setup more in keeping with the Melitz (2003) model. In this framework, reduced trade costs result in increased competition from imports along with greater access to export markets. As in DMS, the ability and incentive for firms to vigorously compete for the best workers depend on their revenues relative to those of their competitors. As explained above, increased access to export markets unambiguously results in more assortative matching since the most productive firms gain revenue relative to those of the least productive firms. In contrast, the effect of increased import competition is ambiguous. On the one hand, increased competition reduces revenues derived from domestic sales by the same proportion for all firms. Since revenue from domestic sales is increasing in productivity, and since all firms suffer the same percentage loss, the absolute loss of revenue is largest for the most productive firms in the industry. This relatively large loss of revenue erodes the capacity and incentive for more productive firms to compete with less productive firms for the best workers. Greater import competition would therefore diminish the degree of assortative matching. On the other hand, firms are only harmed by more intense competition during periods when they are actively producing. In Davidson and Matusz, more productive firms are (endogenously) more selective in hiring, therefore they spend a smaller fraction of their time producing and their losses are softened. The existence of this "capacity utilization" effect could attenuate the revenue loss for the most productive firms, again shifting the motivation and ability to compete for the best workers back in the direction of the more productive firms.

Because of the conflicting forces at work when the market experiences greater import competition, we would expect a reduction in trade costs that primarily results in greater exports to have a larger positive impact on assortative matching than a trade cost that primarily results in more intense domestic competition from foreign firms.

While we do not intend in this paper to test the mechanisms at work in either the DMS or the HIR models, the two frameworks do suggest certain relationships that we should be looking for with respect to matching and openness. Thus, while these results will help guide our empirical work, our main purpose is to determine if there is any support in the data to connect a reduction in trade costs to increased assortative matching.

3. Empirical specification, data and measurement

To examine the relationship between matching and openness and whether the relationship differs based on the trade status of an industry, we use the following specification:

$$Matching_{gt} = \alpha_0 + \alpha_1 Open_{gt} + \alpha_2 Comp\_adv_g \cdot Open_{gt} + D_t + D_g + \mu_{gt} \tag{1}$$

where g indexes industries; t indexes years; $Matching_{gt}$ represents the degree of matching between workers and firms; $Open_{gt}$ measures the degree of openness; $Comp\_adv_g$ indicates the trade status of industry g; D_t and D_g represent year and industry fixed effects; and μ_{gt} is the error term that includes all unobserved factors that may affect the degree of matching. Details about the measurement of the degree of matching, openness, and the industry trade status are given in the sections on data and measurements.

The year fixed effects control for omitted macroeconomic factors that may affect the degree of matching. The industry fixed effects may capture the cross-industry difference in the degree of matching as a result of differences in production technology across industries. Because specification (1) controls for both year and industry fixed effects, identification of the openness effect on matching relies on within-industry over-time variation in the degree of matching and openness. In addition, we include an interaction between openness and the trade status of an industry in Eq. (1) to examine the prediction of the DMS model that more openness increases the degree of matching for industries with greater comparative advantage. The prediction about how the effect of openness should vary systematically across industries by trade status can also help us to separate the effect of openness on the degree of matching from the effect of other factors, e.g., skill-biased technical change, because the impact of those factors on the degree of matching does not differ systematically between industries by their trade status.

3.1. Data sources

We use a matched employer–employee database with detailed information on Swedish firms and establishments linked with a large sample of individuals for the period 1995–2005.[13] To ensure that our sample remains consistent over time, we restrict our analysis to firms with at least 20 employees. The data on individual workers contain wage statistics based on Statistics Sweden's annual salary surveys and are supplemented by material from a series of other data registers. The data set covers more than two million individuals and includes information on worker wages, education, occupation, sector, and demographics.

Firm data are based on Statistics Sweden's financial statistics, covering all Swedish firms and containing variables such as productivity, investments, capital stock, number of employees, value added, profits, sales, a foreign ownership dummy, multinational status, and industry

[13] There are at least two major advantages to using the period 1995–2005. Firstly, the firm data set includes the whole population of firms (previous years include only a sample of the smaller firms). Secondly, Sweden joined the EU in 1995 and changes in tariffs can then be considered exogenous.

affiliation. See Table A1 in the Appendix for a description of the variables.

3.2. Measuring the degree of matching

The degree of matching between workers and firms can be measured simply based on observed worker and firm characteristics. For example, high-tech firms can be characterized as those with higher productivity and high-skilled workers can be characterized as those with more years of education. However, the degree of matching may also be affected by unobserved worker and firm attributes. In fact, previous studies on assortative matching (e.g., Goux and Maurin, 1999; Abowd et al., 2002; Andrews et al., 2006) focus on the correlation between unobserved firm and worker effects. Our objective, however, is to examine if good workers tend to work for good firms. In the theoretical literature that motivates our work, workers and firms meet randomly, but matches are consummated based on all the information that workers and firms observe about each other. For example, all firms in DMS know the ability of potential hires, and all firms in HIR know whether or not potential hires pass the screening test. Our empirical implementation should therefore take account of all available information when formulating measures of worker and firm quality. Thus, unlike the previous literature on assortative matching, our benchmark measure is based on both observed and unobserved worker/firm attributes. In Table 2 we will show that our empirical results are similar whether we use the benchmark measure or use the measure based on just unobservables.[14] Furthermore, in light of empirical evidence that workers mostly move within industries, we construct the measure at the industry level rather than at the national level as done in the previous literature.[15]

To obtain estimates of unobserved worker and firm attributes, we run the following regression:

$$\log w_{ht} = x_{ht}\eta + \theta_h + Z_{j(h,t),t}\lambda + \phi_{j(h,t)} + \delta_t + \upsilon_{ht} \tag{2}$$

where $\log w_{ht}$ is the log wage of worker h at time t, $j(h, t)$ is worker h's employer at time t, x_{ht} is a vector of observable time-varying worker characteristics, θ_h is the worker fixed effect, $Z_{j(h,t),t}$ is a vector of observable time-varying firm characteristics, $\phi_{j(h,t)}$ is the firm fixed effect, δ_t is the year fixed effect, and υ_{ht} is the error term. Eq. (2) is a three-way fixed effects model which extends the Abowd et al. (1999) specification by adding firm-specific time-varying variables.

To avoid possible bias arising from differences in the number of work hours, the dependent variable is measured as full-time equivalent wages. Time-varying worker characteristics include experience squared, higher-degree polynomials of experience, and a dummy variable for blue-collar occupations.[16] An obvious measure of worker ability is educational attainment. However, it is extremely rare for Swedish workers to increase their formal level of schooling after entering the labor force. In our sample, education is essentially time invariant and is therefore subsumed in the worker fixed effects.

Bearing in mind that we are trying to tease out a measure of worker quality, it is worth explaining why we treat the experience and blue collar variables as components of that measure. Experience could contribute to wage determination simply because of union rules or social norms dictating higher wages for more experienced workers. But experience is a measure of worker quality to the extent that on-the-job training or learning-by-doing is significant. Similarly, though the blue collar variable is not a characteristic of the worker per se, it may be correlated with time-varying unobservable worker characteristics. For example, comparing two workers of equal experience, one might be better able to absorb the information and develop the skills needed to be promoted from blue collar to white collar work.

Turning our attention to the firm, time-varying characteristics include capital intensity, firm size (number of employees), labor productivity (value added per worker), share of high-skilled workers (i.e., share of the labor force with at least 3 years of post-secondary education), a manufacturing indicator, the share of female workers and its interaction with the manufacturing indicator.

There are several estimation issues surrounding specification (2). Our Swedish data for 1995–2005 consist of almost 10 million individual-year observations. Computer memory restraints preclude using the least-square dummy variable (LSDV) approach to estimating a model with millions of individual effects and thousands of firm effects. To solve this problem we use a memory saving algorithm to estimate three-way fixed effect models in Stata (see Cornelissen, 2008; Andrews et al., 2006). We include firm dummies and sweep out the worker effects by the within transformation. Firm effects are identified from workers who move between firms over the period. Non-movers add nothing to the estimation of the firm effects so the firm effect will not be identified for firms with no movers. Worker effects are estimated from repeated observations per worker, implying that the data must include a sufficient number of both multiple observations of workers and movers of individuals across firms. This approach, labeled as FEiLSDVj[17] by Andrews et al. (2006), gives the same solution as the LSDV estimator and allows us to recover the individual and firm specific effects (θ_h and $\phi_{j(h,t)}$).

Since the identification of worker and firm effects relies on the mobility of workers across firms, increasing the number of observations per worker and the number of movers per firm provides more precise estimates. The median number of observations per worker is four in our sample (see Table A3 in the Appendix). The median value of movers is above 30 and only 3% of the firms have no movers (see Table A4 in the Appendix). More information on movers are given in Table A5 in the Appendix. We find that the majority of movers remain within their 3-digit industry. Moreover, if we identify each 3-digit industry as either a comparative-advantage or comparative-disadvantage industry, we find that roughly 76% of workers who move remain within these more broadly-defined industry categories.

Worker mobility in our sample is high compared to many previous studies and brings the advantage of getting all firms, except the 3% with no movers, into the same grouping: meaning that they are connected by worker mobility. For the period 1995–2005, the mover group consists of over 9.45 million person-year observations and 8465 unique firms. The group of firms with no movers only consists of 1917 person-year observations and 309 unique firms. This is important since the correlation coefficient between firm and person effects can only be estimated within groups (see e.g. Cornelissen, 2008; Cornelissen and Hubler, 2011). In addition, as we noted in the Introduction, the AKM approach has been criticized on several grounds, one of which is "limited mobility bias," which tends to lead to zero or negative correlation coefficients between unobserved worker and firm fixed effects (i.e., $\phi_{j(h,t)}$ and θ_h) when mobility is low (see Andrews et al., 2008). The high level of mobility in the Swedish data implies that our results are less susceptible to this criticism than previous empirical studies of assortative matching. Finally, we follow Cornelissen and Hubler (2011) and only include workers that are observed in at least two periods and firms that have at least five movers.

[14] In Table A11 in the Appendix, we use a measure based on observables where firm quality is captured by total factor productivity (TFP) and worker quality is captured by years of schooling. Our main results hold. See Section 4.10 for more details.

[15] See Levinsohn (1999), Haltiwanger et al. (2004), Wacziarg and Wallack (2004), Goldberg and Pavcnik (2005), and Menezes-Filho and Muendler (2007) for evidence on worker mobility.

[16] Experience is constructed as age minus number of years of schooling minus seven. Because the years of schooling rarely change in the sample, with both individual and year fixed effects included, experience varies directly with the year fixed effects, that is, the impact of experience on wages is captured by the year fixed effects. Therefore, experience is excluded from Eq. (2).

[17] The "abbreviation stands for Fixed Effect for individual i combined with LSDV for firm j. We use the program felsdvreg (see Cornelissen, 2008), which is a memory saving algorithm to estimate FEiLSDVj in Stata.

The results from the individual wage regressions for the period 1995–2005 are presented in Table 1. Column 1 reports the simple ordinary least squares (OLS) estimates in which both firm and worker fixed effects are excluded. As expected, more experienced workers earn higher wages, but the return to experience has a declining rate. Blue-collar workers earn lower wages than white-collar workers. Moreover, larger firms, more productive and capital intensive firms, and firms with a bigger share of more skilled workers pay higher wages.

Column 2 displays the estimates of the three-way fixed effect model in Eq. (2). The coefficient on the dummy variable for blue-collar occupations remains negative, although the magnitude of the coefficient is greatly reduced after controlling for unobserved worker fixed effects. Similar to the OLS estimates, bigger firms and those with higher productivity and a higher share of skilled workers pay higher wages, but in contrast to column 1, the estimated coefficient on capital intensity turns negative after controlling for firm effects. In addition, the estimates in column 2 suggest that in the manufacturing sector firms with a higher share of female workers pay a lower wage.

Based on the estimates of Eq. (2) as reported in column 2 of Table 1, we compute the measure of human capital based on both observed worker abilities ($x_{ht}\eta$) and unobserved worker attributes (θ_h). Workers with higher human capital level are considered as more skilled. At the same time, firms that pay a higher wage premium (i.e. higher $Z_{j(h,t),t}\lambda + \phi_{j(h,t)}$) are considered as better firms. Our benchmark measure of the degree of matching is calculated as the correlation coefficient between worker total effects ($x_{ht}\eta + \theta_h$) and firm total effects ($Z_{j(h,t),t}\lambda + \phi_{j(h,t)}$). On the aggregate level, the correlation coefficient is around 0.10, which indicates positive assortative matching at the national level. In order to compare our estimates with the prior literature, we also calculate the correlation between unobserved firm and worker effects ($\phi_{j(h,t)}$ and θ_h). The estimated correlation coefficients of unobserved effects range from 0.03 to 0.06. This positive correlation is in contrast with the finding of no or even negative correlations in many other studies (Goux and Maurin, 1999; Abowd et al., 2002; Barth and Dale-Olsen, 2003; Gruetter and Lalive, 2004; Andrews et al., 2006; Cornelissen and Hubler, 2011). However, our figures are close to the correlation of 0.08 found for France in the study by Abowd et al. (1999). They are also in line with the study by Andrews et al. (2008) who analyze how sensitive the correlation is to the share of movers in the data. They report a positive correlation when they study movers in high turnover plants. Table A6 in the Appendix lists the correlation coefficients for different samples. Overall, the estimated correlation coefficients between firm and worker total effects are robust to the exclusion of firms with few movers or workers with few observations.

Table 1
Individual worker wage regressions 1995–2005.

	OLS	LSDVreg
	(1)	(2)
Experience	0.0243***	
	(0.0001)	
Experience^2/100	−0.0798***	−0.001***
	(0.0009)	(0.0000)
Experience^3/1000	0.0108***	0.0012***
	(0.0003)	(0.0002)
Experience^4/10,000	−0.0007***	−0.0006***
	(0.0000)	(0.0000)
Blue collar	−0.1909***	−0.0273***
	(0.0002)	(0.0003)
Female	−0.1394***	
	(0.0002)	
Capital intensity	0.0063***	−0.0028***
	(0.0001)	(0.0001)
Size	0.0003***	0.0049***
	(0.0000)	(0.0001)
Labor productivity	0.0494***	0.0067***
	(0.0002)	(0.0001)
Share of high skill	0.3376***	0.0739***
	(0.0006)	(0.0012)
Manufacturing	0.0214***	0.0506***
	(0.0003)	(0.0011)
Share of women	−0.1266***	0.1297***
	(0.0005)	(0.0016)
Manufacturing × share of women	0.0327***	−0.1705***
	(0.0009)	(0.0029)
Time dummies	Yes	Yes
Individual fixed effect	No	Yes
Firm fixed effect	No	Yes
Number of observations	9,452,970	9,452,970
R^2	0.4075	

Note: Column 2 reports the estimates of Eq. (2). See Section 3.2 for more details about the estimation.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

3.3. Measuring openness

Our preferred measure of openness is tariffs. A reduction in foreign tariffs imposed on Swedish exports increases market access for Swedish firms. A reduction in Swedish tariffs imposed on foreign imports may intensify import competition for final goods producers. The main advantage of using tariffs is that they can be considered as exogenous after 1995 when Sweden joined the European Union. It is unlikely that a small country like Sweden can have a substantial impact on the level of tariffs set by the EU. In addition, foreign tariffs are not affected by conditions in Swedish industries. We aggregate the six-digit HS tariff data from the UNCTAD TRAINS database up to the three-digit level of SNI (Swedish Industrial Classification) using trade shares as weights.[18] Specifically, to construct the industry-level foreign tariffs, the shares of Swedish exports in 1995 (the first year in the sample) are used as weights. For the industry-level Swedish tariffs on foreign goods, the shares of Swedish imports in 1995 are used as weights. Both foreign tariffs and Swedish tariffs were reduced over the sample period, and tariff reductions vary across industries.

In order to capture the degree of offshoring, our second measure of openness is the share of sales by multinational firms (both foreign and Swedish owned) in total sales in Sweden. Foreign owned multinational firms are defined as firms with above 50% foreign ownership and Swedish multinational firms are defined as Swedish owned firms with affiliates abroad. Over the sample period, the share of sales by multinational firms increased steadily.

3.4. Defining the trade orientation of an industry

We measure the trade orientation of an industry using the value of net exports as a share of total trade (imports plus exports) in 1995 for that industry. This measure has two advantages. First, it captures the extent of comparative advantage or comparative disadvantage an industry has. In trade models that combine monopolistic competition and Heckscher–Ohlin (e.g., Helpman and Krugman, 1985) or the models that further add firm heterogeneity (e.g., Bernard et al., 2007), trade flows can be decomposed into intra-industry and inter-industry trade components, and the inter-industry trade component is considered to be driven by endowment-based comparative advantage. The absolute value of our measure can be interpreted as an inter-industry trade index.[19] The sign of our measure indicates whether the industry has a comparative advantage or a comparative disadvantage while its absolute value measures the extent of comparative advantage or

[18] SNI roughly corresponds to Standard Industrial Classification (SIC).

[19] One version of the Grubel–Lloyd index of intra-industry trade is 1 − |exports − imports| / (exports + imports).

Table 2
Openness and assortative matching: baseline results.

	Firm effect and worker effect	Firm effect and average worker effect	Firm effect and median worker effect	Unobserved firm effect and worker effect	Firm effect and worker effect	Firm effect and worker effect
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign tariffs	0.0144***	0.0416***	0.0469***	0.00724**	0.0163**	0.0127**
	(0.00295)	(0.0122)	(0.0105)	(0.00282)	(0.0031)	(0.0058)
Comparative-advantage × foreign tariffs	0.0347***	0.118***	0.127***	0.0152**	0.0389***	0.0361**
	(0.00732)	(0.0265)	(0.0219)	(0.00708)	(0.0066)	(0.0151)
Year dummies × foreign tariffs	No	No	No	No	No	Yes
Year dummies × comparative-advantage	No	No	No	No	Yes	No
R^2	0.065	0.043	0.037	0.048	0.073	0.076

Note: The dependent variable is the degree of matching. It is measured as the correlation coefficient between firm total effects and worker total effects in columns 1, 5–6, the correlation coefficient between firm total effects and the worker total effects averaged across all workers employed in the firm in column 2, the correlation coefficient between firm total effects and the median worker total effects for all workers employed in the firm in column 3, and the correlation coefficient between unobserved firm and unobserved worker effects in column 4. The tariff data are transformed so that an increase in the independent variable *Foreign tariffs* represents more openness. The variable "comparative-advantage" represents the trade status of an industry which is measured as the value of net exports as a share of total trade for 1995. All of the regressions include industry and year fixed effects. There are 860 observations and 88 industries. Standard errors reported in parentheses are clustered by industries. See Section 3 for more details about data and measurement.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

comparative disadvantage the industry has. As shown in Table A8 in the Appendix, the industries that have the strongest comparative advantage include mining of iron ores, sawmilling and planing of wood, manufacture of pulp, paper and paperboard, and manufacture of builders' carpentry and joinery, etc. These industries are based on Sweden's abundant natural resources. On the other hand, the industries that have the strongest comparative disadvantage include manufacture of knitted and crocheted articles, footwear, jewelry, other wearing apparel and accessories, luggage, handbags, etc. All of these industries are highly labor intensive.

The second advantage of our measure is that unlike Balassa's measure of revealed comparative advantage that looks at exports only; our measure can capture the proportion of trade that is tied to export versus import activities.[20] The DMS model predicts that increased export activity would result in better labor market sorting while an increase in import penetration *might* lead to less efficient sorting. Our measure can help to account for these two competing forces and thus it is particularly relevant for our empirical analysis. For industries with strong comparative advantage, i.e., with a large positive value of net exports as a share of total trade, the effect of increased export activity should lead to a positive relationship between increased market access and the degree of matching. On the other hand, for industries with a strong comparative disadvantage, i.e., with a large negative value of net exports as a share of total trade, the effect of increased import penetration might result in a negative relationship between increased import competition and the degree of matching.

As robustness checks, we define the trade orientation of an industry using a binary variable. We define an industry as having a comparative advantage if it had positive net exports in 1995, and an industry as having a comparative disadvantage if it had positive net imports in 1995. We also define the trade orientation of an industry based on the average of net exports across years. An industry is defined as having a comparative advantage if it had a positive average of net exports over the sample period. Another alternative definition is based on positive or negative net exports across years. An industry is considered as having a comparative advantage if it had more years with positive net exports than with negative net exports over the sample period. These three alternative measures of trade status are highly correlated with 90% of industries having consistent definitions of trade status based on these measures.

4. Empirical results on openness and matching

4.1. Baseline estimates

Table 2 reports the estimation results for Eq. (1). Our baseline estimates include only foreign tariffs as the measure of openness. We omit Swedish tariffs from our baseline specification because, as we report below, their estimated effects are not significantly different from zero. The statistically insignificant effect of Swedish tariffs is consistent with the Davidson and Matusz (2012) model in which import restrictions could have opposing effects on the degree of assortative matching. Note that in Table 2 the tariff data are transformed so that an increase in the independent variable *Foreign Tariffs* represents more openness. We report standard errors clustered at the 3-digit SNI industry level which allows inference robust to serial correlations within industries.

Column 1 of Table 2 displays the results when the degree of matching is measured as the correlation coefficient between worker and firm total effects. The estimated coefficient on the interaction between openness and our measure of comparative advantage is 0.035 with a standard error of 0.007, indicating that the positive effect of reduced foreign tariffs on the degree of matching is significantly stronger in industries with a greater comparative advantage. Using the estimated coefficients on openness and the interaction term, we infer that reduced foreign tariffs can increase the degree of matching for industries with the comparative-advantage measure greater than -0.4 ($=-0.014 / 0.035$). From Table A8 in the Appendix, just 16 industries have a comparative advantage measure below -0.4. Thus, the estimates suggest that for 72 out of the 88 industries in our sample, reduced foreign tariffs have a positive impact on the degree of matching. The positive effect of reduced foreign tariffs on the degree of matching is largest for industries with the strongest comparative advantage. For example, the industry of mining iron ores has the largest positive value of the comparative-advantage measure, 0.936. The estimate suggests that a one standard deviation reduction in foreign tariffs (i.e., 5%) can increase the degree of matching in the industry of mining iron ores by 1.72 standard deviations.[21] For the 20 industries with the largest comparative advantage, matching improves on average by 1.15 standard deviations when tariffs fall by 1 standard deviation.

[20] Using our data we also computed Balassa's measure of revealed comparative advantage. The correlation between the Balassa measure and our measure is remarkably high, 0.73 with a p-value of less than 0.0001. Not surprisingly, using Balassa's measure did not change our regression results.

[21] The estimate in column 1 of Table 2 suggests that for the industry of mining iron ores, a 5% reduction in foreign tariffs may increase the degree of matching by $(0.0144 + 0.0347 \times 0.936) \times 5 = 0.234$, which is 1.72 times the standard deviation of the degree of matching. See Table A2 in the Appendix for the statistics on foreign tariffs and the degree of matching. Note that foreign tariffs are expressed in terms of percentages in the data.

Table 3
Alternative measures of openness.

	Contemporaneous openness			Openness at a 1-year lag		
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign tariffs	0.0144***	0.0146***		0.0138***	0.0138***	
	(0.00295)	(0.00275)		(0.00245)	(0.00234)	
Comparative-advantage × foreign tariffs	0.0347***	0.0351***		0.0403***	0.0401***	
	(0.00732)	(0.00671)		(0.00655)	(0.00593)	
Swedish tariffs		0.0233			0.00546	
		(0.0151)			(0.0130)	
Comparative-advantage × Swedish tariffs		0.00688			0.00419	
		(0.0246)			(0.0261)	
MNE share			0.0699			0.104**
			(0.0579)			(0.0473)
Comparative-advantage × MNE share			0.357**			0.285**
			(0.159)			(0.131)
R^2	0.065	0.070	0.073	0.081	0.081	0.080
Observations	860	860	860	766	766	766
Number of industries	88	88	88	87	87	87

Note: This table examines the robustness of our baseline results to alternative measures of openness. The dependent variable is the degree of matching, which is measured as the correlation coefficient between firm total effects and worker total effects. The variable "comparative-advantage" represents the trade status of an industry which is measured as the value of net exports as a share of total trade for 1995. The tariff data are transformed so that an increase in the independent variables *Foreign tariffs* and *Swedish tariffs* represents more openness. All of the regressions include industry and year fixed effects. Standard errors reported in parentheses are clustered by industries. See Section 3 for more details about data and measurement.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

On the other hand, for industries with the greatest comparative disadvantage, reduced foreign tariffs may have a negative effect on the degree of matching. For example, the manufacture of knitted and crocheted articles has the largest negative value of the comparative-advantage measure which is −0.860. The estimate in column 1 implies that a 5% reduction in foreign tariffs may reduce the degree of matching by 0.56 standard deviations (the computation is similar to footnote 21.)

These results provide strong evidence that greater market access improves the degree of assortative matching in industries with a greater comparative advantage. A reduction in foreign tariffs improves the opportunity for Swedish firms to enter or expand their presence in foreign markets. As the DMS model suggests, good firms will benefit more from the increased access to world markets and hire more highly-skilled workers. On the other hand, weak firms will only serve the domestic market and become less able to attract highly-skilled workers. As a result, the degree of positive assortative matching increases. Although all industries have export activities, industries with greater comparative advantage should have a higher share of firms that export and benefit more from reduced foreign tariffs. Thus, the positive effect of reduced foreign tariffs on the degree of matching is expected to be larger in industries with a stronger comparative advantage.

In addition, the estimates also imply that the effect of reduced foreign tariffs on the degree of matching is weaker for industries dominated by intra-industry trade than for industries with more inter-industry trade. Since intra-industry trade is largely driven by scale economics and is between countries with similar endowments, our result is consistent with the view that intra-industry trade tends to have smaller effects on the labor market than endowment-based inter-industry trade.

Column 2 of Table 2 reports the results when the degree of matching is alternatively measured by correlating the firm total effects with the worker total effects averaged across all workers employed in the firm. Column 3 shows the estimates when the degree of matching is measured by a correlation between the firm total effects with the total effect of the median worker employed by the firm. In column 4 we follow the literature on assortative matching and construct the measure of the degree of matching based on unobserved firm and worker effects. All of these alternative measures generate fairly similar results for the effect of openness on the degree of matching. The estimates suggest that reduced foreign tariffs have a stronger positive effect on the degree of matching for industries with greater comparative advantage. In addition, reduced foreign tariffs significantly increase the degree of positive assortative matching for the majority of industries in our sample, but may reduce the degree of matching for a few industries with the strongest comparative disadvantage. Thus, these results are consistent with our baseline estimates as shown in column 1.

The tariffs show a declining trend over the studied period. It is possible that our results might be caused by other trending variables. We have therefore in column 5 included an interaction term between each of the 11 year dummies and our measure of comparative advantage, and in column 6 we have included an interaction term between year dummies and foreign tariffs. The results remain robust.

We also compute the degree of matching based on the estimates from wage regressions that exclude some of the firm/worker characteristics, e.g., the share of high-skilled workers, manufacturing indicator, share of female workers, and its interaction with the manufacturing indicator. Our results are robust to these alternative measures (not shown).

Further, we divide the sample into comparative advantage and comparative disadvantage industries based on positive and negative net exports in 1995, and run separate regressions for the comparative advantage and comparative disadvantage industries. We find that reduced foreign tariffs have a positive and statistically significant effect on the degree of matching in comparative advantage industries, but a negative and statistically significant effect in comparative disadvantage industries.

Another issue to consider is a potential bias due to estimation errors of the correlation coefficient used in the second-stage regression of the degree of matching on openness. Note that the correlation coefficient is constructed using estimates of the first-stage wage regression. Hansen (2007) suggests that estimation errors of the correlation coefficients may be ignored for moderate or large cell size since the bias will likely be a small concern.[22] Further, we take two different approaches to adjusting the standard errors of the second stage regression in order to account for the standard errors of the estimated correlation coefficient. Our first approach is to resample the worker and firm effects (estimated from the wage regression) at the industry-year level and generate 100 different correlation coefficients for each industry-year cell. From these 100 replications (bootstrapping) we then calculate the variance of the correlation coefficients for each industry-year cell and use these as

[22] Our first-stage wage regression corresponds to Eq. (1) in Hansen (2007), and our second-stage regression of the degree of matching on openness corresponds to Eq. (2) in Hansen (2007). With 9 million observations and 860 industry-year cells, we have an average cell size of approximately 10,500 observations, which is substantially larger than the average cell size (512 observations) considered by Hansen (2007).

Table 4
Alternative measure of comparative advantage.

	Export shares	Import shares	Export and import shares
	(1)	(2)	(3)
Foreign tariffs	0.0126***		0.0128***
	(0.0026)		(0.0024)
Export share × foreign tariffs	0.0693***		0.0702***
	(0.0146)		(0.0134)
Swedish tariffs		0.0241	0.0230
		(0.0149)	(0.0147)
Import share × Swedish tariffs		−0.0404	−0.0138
		(0.0499)	(0.0491)
R^2	0.065	0.053	0.070

Note: In this table we use export share and import share to measure the extent of comparative advantage or comparative disadvantage an industry has. Export share is defined as exports as a share of total trade (imports plus exports) in 1995 for that industry. Import share is defined as imports as a share of total trade in 1995 for that industry. Both export share and import share are expressed as deviations from their sample means. The dependent variable is the degree of matching. It is measured as the correlation coefficient between firm total effects and worker total effects. The tariff data are transformed so that an increase in the independent variables *Foreign tariffs* and *Swedish tariffs* represents more openness. All of the regressions include industry and year fixed effects. There are 860 observations and 88 industries. Standard errors reported in parentheses are clustered by industries. See Section 3 for more details about data and measurement.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

weights in the second stage regression. Our second approach is to give higher weights to large industries which might be estimated with more precision. Industry size is measured using the number of workers, sales, capital stock, value of exports, or value of total trade. The results remain robust as seen in Tables A9 and A10 in the Appendix. Because the results are not significantly different from our benchmark result in column 1 of Table 2, following Hansen's (2007) suggestion we will ignore estimation errors of the correlation coefficient and estimate the second stage regression using standard panel data methods.

4.2. Alternative measures of openness

We now examine the robustness of our baseline results to alternative measures of the degree of openness. The results are displayed in Table 3. Column 1 reports the results carried from column 1 of Table 2 when openness is measured by foreign tariffs. In column 2 we add Swedish tariffs on foreign goods as an additional measure of openness. We find that the estimated coefficients on foreign tariffs and the interaction with comparative advantage remain unchanged. However, we find no significant effect of reduced Swedish tariffs on the degree of matching. One possible explanation for this weak result is that reduced Swedish tariffs can have opposing effects on Swedish firms within an industry as suggested by the Davidson and Matusz (2012) model.

In column 3 we measure openness using Swedish sales of multinational firms (both Swedish and foreign owned) as a share of total Swedish sales of all firms producing in Sweden. An increased share of multinational sales may indicate increased economic activities associated with outsourcing or offshoring. Thus, this measure of openness helps to capture another important aspect of increasing economic integration. The estimates in column 3 show that increased share of multinational sales have significantly stronger positive effects on industries with greater comparative advantage, which is consistent with the result when openness is measured by foreign tariffs. However, unlike foreign tariffs, the share of multinational sales may be endogenous. If multinational production activities benefit from better matching between firms and workers, the estimates in column 3 may overstate the impact of increased outsourcing or offshoring on the degree of matching. To deal with the possible reverse causality, we replace the contemporaneous measure of multinational sales with the measure at a one-year lag. As shown in column 6, the estimated coefficient on lagged multinational sales is 0.104 with a standard error of 0.047, which is statistically significant and larger than the estimate of 0.070 for contemporaneous multinational sales as reported in column 3. The estimated coefficient on the interaction with the measure of comparative advantage is 0.285 with a standard error of 0.131, which is also statistically significant but smaller than the estimate of 0.357 for contemporaneous multinational sales reported in column 3. Based on the estimates in columns 3 and 6, it can be shown that for industries with a stronger comparative advantage (i.e., with the comparative-advantage measure greater than 0.47) contemporaneous multinational sales are estimated to have a larger positive effect than lagged multinational sales.[23] Therefore, this result provides some supporting evidence that using the contemporaneous measure of multinational sales is likely to overstate the positive effect of increased outsourcing or offshoring activities on the degree of assortative matching for industries with greater comparative advantage.

In columns 4–5 of Table 3 we replace the contemporaneous measures of tariffs with those at a one-year lag. The results are little changed. In contrast to multinational sales, we find that for industries with greater comparative advantage lagged foreign tariffs in fact have a larger positive impact on the degree of matching than contemporaneous foreign tariffs. Overall, our baseline results are robust to alternative measures of openness.

4.3. Alternative measure of comparative advantage

In the above we measure the extent of comparative advantage of an industry using the share of net exports in total trade for that industry. In Table 4 we examine exports and imports separately to assess the relative impact of each on the degree of matching. In the specifications, exports as a share of total trade is interacted with foreign tariffs and imports as a share of total trade is interacted with Swedish tariffs.[24] As suggested by the previous theoretical discussion, increased export activity improves the firm–worker matching while increased import penetration has an ambiguous effect on matching.

The results in Table 4 show an expected positive effect of openness for export intensive industries: the interaction term between export share and foreign tariffs is statistically significant in columns 1 and 3. At the same time, we do not find that lower Swedish tariffs have any significant effect on matching in industries with high import shares. The weak result for imports could be attributable to the two opposing effects of imports on firms within an industry, as suggested by Davidson and Matusz (2012). On the one hand, increased imports generate a competition effect on producers that directly compete with imports and worsen matching because high-tech firms would suffer more from import competition. On the other hand, high-tech firms are endogenously more selective in their hiring and spend less time producing. Since firms are harmed by import competition only during the period when they are producing, the revenue loss for the high-tech firms would be attenuated, which could provide them the incentive to hire more skilled workers.[25]

[23] The estimated effect of contemporaneous multinational sales on the degree of matching is $0.070 + 0.357 \times Comp - adv_g$. The estimated effect of lagged multinational sales on the degree of matching is $0.104 + 0.285 \times Comp - adv_g$. It can be shown easily that for industries with the measure of trade status, $Comp - adv_g$, greater than 0.47, contemporaneous multinational sales are estimated to have a larger positive effect on the degree of matching.

[24] To facilitate interpretation, both export share and import share are expressed as deviations from their sample means. Thus, the coefficient on *Foreign tariff* captures the effect of reduced foreign tariffs on the degree of matching for an industry with an average value of export shares, and the coefficient on *Swedish tariff* reflects the effect of reduced Swedish tariffs on the degree of matching for an industry with an average value of import shares.

[25] We also measure the trade orientation of an industry using exports (or imports) as a share of domestic absorption (i.e., domestic production plus imports minus exports) in 1995 for that industry. To obtain data on domestic production, we use data from Stan that have information on both trade and production, but at a more aggregated level. The results are consistent with those reported in Tables 2–3. In particular, we find that more trade openness improves matching for industries with a higher export share. The results are available upon request.

Table 5
Statistics of the estimates of the wage regression with and without match effects.

	AKM model			Orthogonal match effects model				Hybrid mixed model			
	Std. dev. of firm effects	Std. dev. of person effects	Correlation of person–firm effects	Std. dev. of firm effects	Std. dev. of person effects	Correlation of person–firm effects	Std. dev. of match effects	Std. dev. of firm effects	Std. dev. of person effects	Correlation of person–firm effects	Std. dev. of match effects
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
1995	0.07	0.47	−0.02	0.07	0.46	−0.01	0.06	0.10	0.43	0.06	0.04
1996	0.08	0.47	0.00	0.08	0.46	−0.00	0.06	0.11	0.43	0.06	0.04
1997	0.08	0.47	0.00	0.08	0.46	0.01	0.05	0.11	0.43	0.07	0.04
1998	0.08	0.47	0.01	0.08	0.46	0.01	0.05	0.12	0.43	0.08	0.04
1999	0.08	0.47	0.04	0.08	0.46	0.04	0.05	0.12	0.43	0.10	0.04
2000	0.09	0.48	0.06	0.08	0.46	0.06	0.05	0.12	0.43	0.12	0.04
2001	0.09	0.47	0.06	0.09	0.46	0.06	0.04	0.12	0.43	0.11	0.04
2002	0.09	0.47	0.07	0.09	0.46	0.07	0.04	0.13	0.43	0.12	0.04
2003	0.09	0.47	0.07	0.09	0.46	0.07	0.05	0.13	0.43	0.14	0.04
2004	0.09	0.47	0.07	0.09	0.46	0.08	0.05	0.13	0.43	0.14	0.04
2005	0.09	0.47	0.07	0.09	0.46	0.07	0.06	0.13	0.42	0.13	0.04

Note: The table shows results from different versions of estimations of Eq. (2). Columns 1–3 refer to the basic AKM model, and columns 4–7 refer to the two different versions of our match effect model. For each model we present the standard deviation of the firm and person effects and the correlation between the two effects. For the two match effect models we also present the standard deviation of the match effects.

4.4. Accounting for match effects

Up to this point our analysis fits into the traditional search-theoretic literature on assortative matching where output is a function of technology, worker quality and firm quality with complementarities between worker skill and firm productivity typically assumed. Thus, as we have emphasized, efficient matching implies that good workers should be matched with good firms. The question is whether the market leads to efficient matching when search frictions are present, and the key is to focus on the correlation between the worker and firm types. The AKM paper was designed to test this prediction and included only worker fixed effects and firm fixed effects in the main empirical specification. However, workers may match with firms on the basis of a match-specific productivity effect and workers may receive some share of the rents from a successful match (e.g., Mortensen and Pissarides, 1994). In the empirical literature on assortative matching this point was first emphasized by Woodcock (2008a) who argued that excluding match effects from the analysis could introduce a bias in the estimation of the firm effect.

In this section we add match effects to our analysis as a robustness check. Before doing so, it is worth noting that match effects have played a significant role in a number of recent trade papers including Frías et al. (2009), Helpman et al. (2010), Krishna et al. (2014) and Liu and Trefler (2011).[26] In fact, the main model in Helpman et al. (2010) includes a match effect but no separate worker effect (in that, once matches break-up, workers return to the pool of unemployed where all are identical). They provide an explanation for why match effects might be linked to trade costs: falling trade costs generate an incentive for better firms to screen more intensely and reject more poor matches. The implication is that globalization should lead to an increase in the size of the average match effect.

We generalize the AKM type wage regression by including a match effect which is an interaction between workers and firms. The match effect measures returns to time-invariant and unobserved characteristics of worker–firm matches that are common to all periods of an employment spell. Including a match effect allows us to address Woodcock's (2008a,b) criticism of the AKM approach that when match effects are omitted, all other effects are potentially biased. The identification of person, firm and match effects requires a distinction between lucky matches (a high match effect) and good workers/firms. Woodcock proposes two methods: one is the orthogonal match effect estimator, and the other is the hybrid mixed effect estimator. The orthogonal match effect estimation has two stages. First, the return to the observed worker and firm characteristics is estimated using the within individual/firm ("spell") estimator. The remaining wage residual is then decomposed into person, firm and match effects based on the assumption that match effects are orthogonal to the firm and worker effects.

The hybrid mixed effect estimator combines features of traditional fixed and random effect estimators. It treats the worker, firm and match effects as random. Similar to Hausman and Taylor's (1981) correlated random effects estimator, the hybrid mixed effect estimator allows arbitrary correlation between the random effects and time-varying observable firm and worker characteristics. Thus, it differs from a traditional random effect estimator that imposes restrictions on the relationship between observables and the unobserved heterogeneity components. The hybrid mixed effect approach again first estimates the return to observed worker and firm characteristics using the within-spell estimator. It then decomposes the wage residual into person, firm, and match effects under the conditional moment assumptions about the random effects (see Eqs. (10) and (11) in Woodcock, 2008b) and the assumption that the random effects are uncorrelated with the error term.[27]

Table 5 reports the statistics of the estimates from wage Eq. (1) with and without match effects added. Columns 1–3 present statistics for the AKM model, whereas columns 4–11 show statistics for our two match effect models. For each model we present the standard deviations of firm and worker effects and the correlation between the two effects. For the two match effect models we also present the standard deviations of match effects. Columns 3 (without match effect) and 6 (orthogonal model of match effects) are nearly identical. In contrast, the correlations reported in column 10 (hybrid model of match effects) are uniformly higher than those reported in column 3, though the time pattern of change is qualitatively identical to the pattern observed in column 3. In particular, all of the three models suggest that the correlation of person–firm effects increases steadily over the entire sample period, indicating that good workers (those with a high worker effect) are increasingly more likely to be employed at good firms (those with a high firm effect). This type of increase in assortative matching between workers and firms is also documented in Card et al. (2014) among others.

[26] Krishna et al. (2014) examine the wage effects of trade reform. Unlike our work, their primary interest is in estimating the differential effect of trade liberalization controlling for match effects rather than in estimating separately the worker and firm effects. They find that trade liberalization improves the match effects in exporting firms.

[27] Estimating the hybrid mixed effect model formally proceeds in three steps: (i) the return to observables are estimated using the within individual/firm estimator, (ii) the variance of the different random effects are estimated on the wage residuals using restricted maximum likelihood (REML), and (iii) the model solves for the random effects.

Table 6
Accounting for match effects.

	Baseline	Orthogonal match effects		Hybrid mixed match effects	
	(1)	(2)	(3)	(4)	(5)
Foreign tariffs	0.0144***	0.0156***	0.0159***	0.0112***	0.0100***
	(0.00295)	(0.00295)	(0.00279)	(0.00319)	(0.00296)
Comparative-advantage × foreign tariffs	0.0347***	0.0328***	0.0334***	0.0182**	0.0149**
	(0.00732)	(0.00725)	(0.00672)	(0.00766)	(0.00732)
Swedish tariffs			0.0222		−0.00187
			(0.0153)		(0.0138)
Comparative-advantage × Swedish tariffs			0.00441		0.0335*
			(0.0249)		(0.0190)
R^2	0.065	0.063	0.068	0.059	0.065

Note: The dependent variable is the degree of matching. See Section 4.4 for more details about the measurements of the degree of matching when match effects are accounted for. The tariff data are transformed so that an increase in the independent variables *Foreign tariffs* and *Swedish tariffs* represents more openness. The variable "comparative-advantage" represents the trade status of an industry which is measured as the value of net exports as a share of total trade for 1995. All of the regressions include industry and year fixed effects. There are 860 observations and 88 industries. Standard errors reported in parentheses are clustered by industries. Also see Section 3 for more details about data and measurement.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

We then examine the relationship between trade openness and the degree of matching (measured as the correlation coefficient between worker and firm total effects). The results are presented in Table 6. For comparison, column 1 reports the baseline estimates carried from column 1 of Table 2. Overall, the table shows that our main results still hold when the match effects are accounted for. In particular, in columns 2–3 when the degree of matching is calculated using estimates from the wage regression that assumes the match effects to be orthogonal to the firm and worker effects, the results are almost identical to the baseline results as shown in column 1. In columns 4–5 when the measure of matching is computed based on the wage regression that allows the worker and firm effects to be correlated with the match effects, the estimated effect of openness is somewhat smaller than the baseline result. However, the main message remains the same. Again, we find that reduced foreign tariffs have significantly stronger positive impacts on the degree of matching for industries with a greater comparative advantage, and for the majority of industries in our sample, reduced foreign tariffs improve the degree of matching. Therefore, our main results are not the result of rent sharing between workers and firms triggered by increased openness.

It would be interesting to know if there is any correlation between openness and the quality of matches represented by the match effect. For example, Helpman et al. (2010) predict that greater openness induces firms to screen more intensively, becoming more selective in the quality of matches that they accept. This would suggest that the average quality of match should increase with openness, a result that is independent of worker and firm effects since they assume homogeneous workers and firms. Unfortunately, the empirical methodology used to isolate the match effect constrains the average match effect to equal zero (see Woodcock, 2008b; Card et al., 2014), therefore it is impossible for the estimated average match effect to change over time. However, we might infer from Helpman et al. (2010) that the variance of the match effect would fall as firms screen more intensively, eliminating the poorest matches. As shown in columns 7 and 11 of Table 5, we find no evidence that the distribution of the match effect has changed over time, a result that would appear to be at odds with Helpman et al. (2010).[28]

Another issue to be considered is that the AKM model builds on the assumption that the worker and firm effects are additively separable in the wage regression. Violations of the additive separability assumption in the AKM model would imply relatively large mean residuals for particular types of matches. We follow Card et al. (2014) by examining the errors for different groups of workers at different firms. Specifically, we divide the worker and firm effects (estimated from the AKM model) into deciles and compute the mean residuals from the AKM model in each of the 100 worker–firm decile cells. As displayed in Fig. 2, the mean residuals in each cell are very small (less than 0.5% in magnitude). Thus, similar to Card et al., we do not observe any systematic departures from the additive separability assumptions of the AKM model.[29]

To sum up, since we do not find any significant change in the distribution of match effects over time, our results indicate that any improvement in labor market efficiency due to falling trade costs comes from better matching between workers and firms of given abilities rather than improvements in match-specific productivity.

4.5. Technical change, deregulations, and product market competition

In Acemoglu (1999) and Albrecht and Vroman (2002) search models are developed in which skill-biased technical change increases the gap between productivity of high-skilled and low-skilled workers; and, as a result, the degree of positive assortative matching rises. In order to separate the effect of openness from the effect of technical change on the degree of matching, we add several industry-level measures of technical change as controls in Table 7. As shown in Table 7, none of the measures have any significant impact on the degree of matching. Including interaction terms with comparative advantage and our variables on skill-biased technical change has no impact on the core results. On the other hand, our estimates of the effect of openness remain unchanged.

There were no major reforms of the Swedish economy during the period we are examining. However, shifts in domestic market competition may coincide with the change in openness to trade and foreign investment during the sample period. It is possible that increased or reduced domestic market competition can affect the profitability of high-tech and low-tech firms and further affect what types of workers they want to hire. In order to disentangle the effect of domestic market competition on the degree of matching from the effect of openness, we add measures of domestic deregulations and product market competition as controls. The estimates are shown in Table 8.

The regulatory indicator captures the amount of anti-competitive regulations at the two-digit industry level and is constructed by

[28] Table 5 also reports that the estimated standard deviations of worker and firm effects change little. This result would be expected if the set of firms and workers in our sample does not change.

[29] Based on these and additional tests, Card et al. (2014) conclude that the separability assumptions of the AKM model are nearly met in their data, and that adding a match specific component yields only a small improvement in the fit of the model.

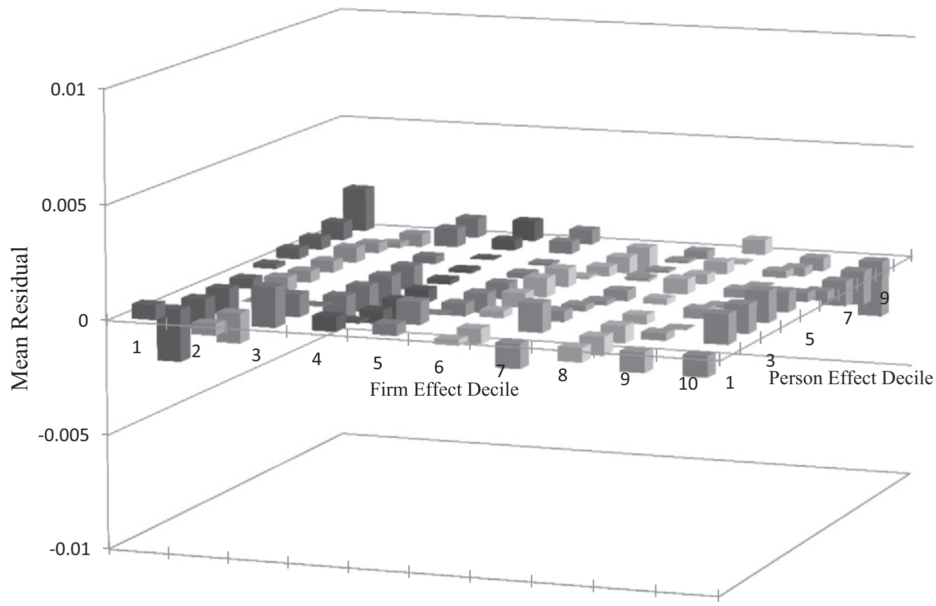

Fig. 2. Mean residual by worker/firm deciles, 1995–2005. The figure shows mean residuals from the estimated AKM model with cells defined by decile of estimated firm effects interacted with decile of estimated person effects.

the OECD. A higher value of the index indicates a higher degree of regulations.[30] Column 1 of Table 8 shows that more anti-competitive regulations lead to a higher degree of positive assortative matching. This may indicate that high-tech firms benefit more from anti-competitive regulations and hire more highly-skilled workers. On the other hand, our results for the effect of openness remain unchanged.

We also construct a measure of product market competition at the two-digit industry level by following Boone (2008) and Boone et al. (2007). This measure is based on the within-industry elasticity of profits with respect to marginal costs. [31] The higher the absolute value of this elasticity, the fiercer the competition. The results reported in columns 2–3 of Table 8 indicate that this measure has no significant effect on the degree of matching. Furthermore, including interaction terms with comparative advantage and our measures on competition and regulation has no major impact on the results. Again, our results for the effect of openness are unchanged.

4.6. Separate estimations for high- and low-skilled workers

Lise et al. (2013) document productive complementarities between job and worker characteristics for high-skilled groups, but not for the lowest-skilled group. This is because college graduates generally have more stable careers and move to better matches when they have the opportunity, while high school graduates are more likely to be separated to unemployment. As noted by Card et al. (2014), because our fixed effects estimator conditions on the actual sequence of firms at which each worker is observed, such pattern of worker movement does not violate the orthogonality conditions for the identification of the parameters in Eq. (2) (see Card et al., 2014 for more details).

In Table 9 we run regressions separately for high-skilled and low-skilled workers based on their education levels, in order to examine whether our results are related to the mobility of high-skilled workers. The dependent variables are the correlation coefficients between the estimated total firm and worker effects for workers with different education levels. As shown in Table 9, we find that the positive relationship between openness and matching originate from more educated workers (columns 4–5), whereas no significant association is found for less educated workers (columns 2–3).

4.7. Alternative definitions of the trade status of an industry

In the above analysis we have used a continuous measure of the trade status of an industry. In this section we report the results when the trade status of an industry is defined using a binary variable. The results are reported in Table 10. In columns 1–2 an industry is defined as having a comparative advantage if this industry had positive net exports in 1995, and an industry is defined as having a comparative disadvantage otherwise. In column 1 foreign tariffs are used as the measure of openness. The estimate for comparative advantage industries is 0.022 and statistically significant. However, the estimate for comparative disadvantage industries is −0.001 and statistically insignificant. These results are closely related to the baseline estimate reported in column 1 of Table 2 when the continuous measure of trade status is used. The estimate of 0.022 for comparative advantage industries can be considered as an average effect of reduced foreign tariffs on the degree of matching for industries with a positive continuous measure of the trade status, while the estimate of −0.001 for comparative disadvantage industries can be considered as an average effect for industries with a negative continuous measure of the trade status.[32] Therefore,

[30] Since the regulations are anti-competitive (e.g., barriers to competition, administrative burdens on start-ups, explicit barriers to trade and investment), they tend to lead to an increase in market power for incumbent firms.

[31] To obtain the measure, we run the following regression for each 2-digit SNI industry using OLS: $\ln(\pi_{jt}) = \alpha_j + \alpha_t + \beta_t \ln(c_{jt}) + \varepsilon_{jt}$. Subscript j is a firm-level identifier and t indicates time period. Variable profits, π_{jt}, are defined as value added less the total wage bill. Marginal costs are approximated by average variable costs, c_{jt}, which are defined as the total wage bill plus the costs of variable inputs (sales less value added), divided by sales. Unobserved heterogeneity is taken into account by firm fixed effects, α_j, and time fixed effects, α_t. The absolute value of the estimated profit elasticity, β_t, is used as a time-varying industry measure of product market competition.

[32] Recall that the estimated effect of foreign tariffs on the degree of matching is $0.014 + 0.035 \times Comp - adv_g$ (see column 1 of Table 2). For industries with a positive value of our comparative advantage measure, the effect of foreign tariffs on the degree of matching ranges from 0.014 to 0.035×0.936 where the 0.936 is the comparative-advantage measure for the industry of mining of iron ores (see Table A8). This implies an average effect of $(0.014 + 0.035 \times 0.936) / 2 = 0.023$. Similarly, for industries with a negative value of our comparative advantage measure, the effect of foreign tariffs on the degree of matching ranges from 0.014 to $0.014 + 0.035 \times (-0.860)$ where the −0.860 is the comparative-advantage measure for the manufacture of knitted and crocheted articles. This suggests an average effect of $(0.014 - 0.035 \times 0.860) / 2 = -0.008$.

Table 7
Controlling for technical change at the industry level.

	Reference	ICT	R&D	Growth in capital	Growth in capital intensity	All controls
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign tariffs	0.0144***	0.0144***	0.0138***	0.0144***	0.0141***	0.0136***
	(0.0030)	(0.0030)	(0.0028)	(0.0030)	(0.0029)	(0.0028)
Comparative advantage × foreign tariffs	0.0347***	0.0346***	0.0337***	0.0346***	0.0345***	0.0335***
	(0.0073)	(0.0073)	(0.0070)	(0.0073)	(0.0072)	(0.0069)
ICT		−0.0098				−0.0229
		(0.0384)				(0.0396)
Comparative advantage × ICT		0.0228				0.0019
		(0.0761)				(0.0820)
R&D			0.0000			0.0000
			(0.0000)			(0.0000)
Comparative advantage × R&D			0.0000			0.0000
			(0.0000)			(0.0000)
Growth in capital				0.0022		−0.0009
				(0.0038)		(0.0033)
Comparative advantage × growth in capital				−0.0024		0.0014
				(0.0222)		(0.0199)
Growth in capital intensity					0.0060	0.0060
					(0.0043)	(0.0046)
Comparative advantage × growth in capital intensity					0.0003	−0.0038
					(0.0086)	(0.0088)
Observations	860	860	816	860	860	816
Number of industries	88	88	84	88	88	84
R^2	0.065	0.065	0.079	0.065	0.067	0.082

Note: This table adds proxies for technical change at the industry level. The dependent variable is the degree of matching, which is measured as the correlation coefficient between firm total effects and worker total effects. The variable "comparative-advantage" represents the trade status of an industry which is measured as the value of net exports as a share of total trade for 1995. The tariff data are transformed so that an increase in the independent variable *Foreign tariffs* represents more openness. ICT investment is the investment in computing and communication equipment as a share of total investment. R&D intensity is R&D expenditures per employee. Growths in capital and growth in capital intensity are annualized growth rates. All of the regressions include industry and year fixed effects. Standard errors reported in parentheses are clustered by industries. See Section 3 for more details about data and measurement.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

these results are consistent with those reported in column 1 of Table 2 when the continuous measure of the trade status is used.

In Davidson et al. (2012) we presented some non-parametric evidence on trade and worker–firm matching. Using an alternative measure of the degree of matching based on the shift in the distribution of workers and firms by skills and technology and our binary measure of trade orientation, we obtained results very similar to the estimates reported in column 1 of Table 10.

In column 3, an industry is defined as having a comparative advantage if the industry had a positive average of net exports over the sample period. In column 5 an industry is defined as having a comparative advantage if the industry had more years with positive net exports than with negative net exports over the sample period. Since 90% of the industries have consistent trade status based on these alternative measures, it is no surprise that the estimates based on these alternative definitions of trade status are very close.

Table 8
Controlling for domestic deregulation and product market competition.

	Reference	Regulatory impact indicator	Competition	All controls
	(1)	(2)	(3)	(4)
Foreign tariffs	0.0144***	0.0129***	0.0130***	0.0115***
	(0.0030)	(0.0028)	(0.0023)	(0.0018)
Comparative advantage × foreign tariffs	0.0347***	0.0334***	0.0316***	0.0293***
	(0.0073)	(0.0066)	(0.0058)	(0.0040)
Regime impact		10.1889*		10.5539
		(5.5675)		(6.8722)
Comparative advantage × regime impact		2.0095		1.3862
		(3.0659)		(3.4587)
Product market competition			0.0035	0.0033
			(0.0027)	(0.0027)
Comparative advantage × product market competition			−0.0053	−0.0030
			(0.0077)	(0.0072)
Observations	860	860	769	769
Number of industries	88	88	77	77
R^2	0.065	0.081	0.081	0.093

Note: This table adds measures of domestic deregulations and product market competition at the industry level. The dependent variable is the degree of matching, which is measured as the correlation coefficient between firm total effects and worker total effects. The variable "comparative-advantage" represents the trade status of an industry which is measured as the value of net exports as a share of total trade for 1995. The tariff data are transformed so that an increase in the independent variable *Foreign tariffs* represents more openness. The regulatory indicator captures the amount of anti-competitive regulations and the construction of product market competition follows Boone (2008) and Boone et al. (2007). All of the regressions include industry and year fixed effects. Standard errors reported in parentheses are clustered by industries. See Section 3 for more details about data and measurement.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Table 9
Separate regressions based on worker education levels.

	Reference	Workers with at most compulsory school (9 years)	Workers with at most 2 years of upper secondary school	Workers with at least 3 years of upper secondary school	Workers with at least undergraduate education
	(1)	(2)	(3)	(4)	(5)
Foreign tariffs	0.014***	0.002	0.003	0.011***	−0.002
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Comparative advantage × foreign tariffs	0.035***	−0.007	0.008	0.031***	0.025***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.006)
Observations	860	856	860	860	807
Number of industries	88	88	88	88	83
R^2	0.065	0.011	0.013	0.088	0.058

Note: In this table we run regressions separately for high-skilled and low-skilled workers. The dependent variable is the correlation coefficient between the total firm and worker effects for workers with different education levels. The variable "comparative-advantage" represents the trade status of an industry which is measured as the value of net exports as a share of total trade for 1995. The tariff data are transformed so that an increase in the independent variable *Foreign tariffs* represents more openness. All of the regressions include industry and year fixed effects. Standard errors reported in parentheses are clustered by industries. See Section 3 for more details about data and measurement.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Table 10
Alternative definitions of trade status.

	Positive net exports in 1995		Positive average of net exports		More years with positive net exports	
	(1)	(2)	(3)	(4)	(5)	(6)
Comparative-advantage industry × foreign tariffs	0.0215***	0.0227***	0.0226***	0.0244***	0.0229***	0.0248***
	(0.00635)	(0.00577)	(0.00586)	(0.00527)	(0.00581)	(0.00524)
Comparative-disadvantage industry × foreign tariffs	−0.000929	−0.00107	−0.00118	−0.00141	−0.00122	−0.00146
	(0.00160)	(0.00144)	(0.00145)	(0.00123)	(0.00143)	(0.00121)
Comparative-advantage industry × Swedish tariffs		0.0170		0.0112		0.0110
		(0.0233)		(0.0226)		(0.0228)
Comparative-disadvantage industry × Swedish tariffs		0.0217		0.0232		0.0235
		(0.0152)		(0.0157)		(0.0157)
R^2	0.058	0.062	0.059	0.064	0.059	0.065

Note: This table examines the robustness of our baseline results to alternative definitions of trade status of an industry. In columns 1–2 an industry is defined as having a comparative advantage if this industry had a positive net export for 1995, and it is defined as having a comparative disadvantage if this industry had a negative net export for 1995. In columns 3–4 an industry is defined as having a comparative advantage if this industry had a positive average of net exports over the sample period 1995–2005. In columns 5–6 an industry is defined as having a comparative advantage if this industry had more years with positive net exports. The dependent variable is the degree of matching, which is measured as the correlation coefficient between firm total effects and worker total effects. The tariff data are transformed so that an increase in the independent variables *Foreign tariffs* and *Swedish tariffs* represents more openness. All of the regressions include industry and year fixed effects. There are 860 observations and 88 industries. Standard errors reported in parentheses are clustered by industries. See Section 3 for more details about data and measurement.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Table 11
Excluding outliers.

	Excluding observations with large change in foreign tariffs		Excluding tobacco products, weapons and ammunition		Moving averages of large changes in foreign tariffs	
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign tariffs	0.0267***		0.0192**		0.0263***	
	(0.00901)		(0.00913)		(0.00606)	
Comparative advantage × foreign tariffs	0.0456*		0.0444**		0.0455**	
	(0.0253)		(0.0204)		(0.0196)	
Foreign tariffs at a 1-year lag		0.0102***		0.00915		0.0297***
		(0.00297)		(0.00812)		(0.0103)
Comparative advantage × 1 year lagged foreign tariffs		0.0455***		0.0303*		0.0375**
		(0.00763)		(0.0182)		(0.0184)
Observations	857	764	847	755	860	766
Number of industries	88	87	86	85	88	87
R^2	0.058	0.091	0.05	0.053	0.067	0.075

Note: The dependent variable is the degree of matching. It is measured as the correlation coefficient between firm total effects and worker total effects. In columns 1–2 five observations with large changes in tariffs on Swedish exports are omitted from the regressions, in columns 3–4 the manufacture of tobacco products and the manufacture of weapons and ammunition are omitted, and in columns 5–6 moving averages for the five observations with large changes in foreign tariffs are applied. The tariff data are transformed so that an increase in the independent variable *Foreign tariffs* represents more openness. The variable "comparative-advantage" represents the trade status of an industry which is measured as the value of net exports as a share of total trade for 1995. All of the regressions include industry and year fixed effects. Standard errors reported in parentheses are clustered by industries. See Section 3 in the paper for more details about data and measurement.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Table 12
Openness and assortative matching. First-difference regressions for 1995–2005.

	(1)	(2)
	5-year difference	10-year difference
ΔForeign tariffs	0.0169***	0.0249
	(0.0063)	(0.0149)
Comparative advantage × Δforeign tariffs	0.0450***	0.0430+
	(0.0132)	(0.0262)
Observations	156	74
R^2	0.0705	0.0946

Note: The dependent variable in this table is a 5 or a 10 year difference of the degree of matching, measured as the correlation coefficient between firm total effects and worker total effects. The variable "comparative-advantage" represents the trade status of an industry which is measured as the value of net exports as a share of total trade for 1995. Standard errors reported in parentheses are clustered by industries. All of the regressions include industry fixed effects.
+ A one-tailed t-test for a positive coefficient cannot be rejected (p-value of 0.9475).
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Overall, Table 10 shows that our key result remains unchanged when alternative measures of trade status are used: increased openness has a stronger positive effect on the degree of matching for industries with greater comparative advantage.

4.8. Excluding outliers

A closer look at our industry data revealed a few very large changes in tariff rates on Swedish exports for the manufacture of tobacco products and the manufacture of weapons and ammunition. To examine how robust our results are, we therefore conduct a few additional estimations where the outliers are excluded (Table 11). We use three different approaches: to exclude the specific industry-year observations with large changes in tariff rates; to exclude all years for those two industries that have seen large changes in tariffs at some point during 1995–2005; and to use moving average to smooth large changes in tariffs. The estimates are similar to the results for the full sample.[33]

4.9. First-difference specification

The regressions reported above fully exploit information for each year over the sample period. In order to examine whether the estimates can also capture the long-term relationship between openness and matching, we take simple 5- and 10-year differences of the data and look at the relationship between the change in openness and the change in the degree of matching across industries for 1995–2005. The results are shown in Table 12. Column 1 shows results for the 5-year differences: a positive coefficient on the interaction variable suggests that a reduction in foreign tariffs improves the degree of matching significantly in industries with greater comparative advantage. Column 2 shows a similar positive coefficient for the interaction between foreign tariffs and comparative advantage for the 10-year difference specification, although the estimation precision is somewhat reduced due to a smaller sample. However, a *t*-test of the hypothesis that the coefficient on the interaction term is positive cannot be rejected (a p-value of 0.95), indicating that our key result remains robust even after using the long-difference specification.

4.10. Can we trust the firm effect?

The AKM approach tests for positive assortative matching by calculating the correlation between the firm effect and the worker effect that comes out of a basic wage regression. This approach has been criticized in a recent contribution by Lopes de Melo (2009), which focuses on the AKM approach's ability to correctly rank firms in terms of productivity.[34] In a model with on-the-job-search in which firms earn steady-state profits, very much in the spirit of Shimer and Smith (2000), Lopes de Melo argues that while wages will be monotonically increasing in a worker's human capital, they may be non-monotonically related to firm productivity. The reason for this possibility is that stronger firms, because they have better outside options, will be in a better bargaining position with weak workers and may be able to pay such workers lower wages than other, weaker firms. The implication is that while the worker effect that is generated by the AKM wage regression can be used to rank workers, the firm effect may generate an incorrect ranking of firms.[35] While this is certainly an interesting theoretical possibility, it is hard to know just how important this effect is in practice. Thus, to see if there might be some problem with the firm effects that the AKM approach generates for our study, we examine them in some detail to see if the ranking that they generate for firms seems sensible. In general, one would expect that more-productive firms will tend to be bigger, more capital intensive, export a larger share of their output, and undertake more R&D activities compared with less-productive firms. We find that the estimated firm effects are *monotonically* increasing in labor productivity, firm size in terms of capital stock and employment, capital intensity, R&D intensity, and export intensity.[36] We also calculate the correlation between the firm effects and various firm characteristics, as shown in Table A7 of the Appendix. We find that all of the observed firm characteristics are significantly and positively correlated with our firm quality measure, strongly suggesting that the ranking we are getting from AKM seems to make sense.

Finally, one potential problem with the AKM approach discussed above comes from using wages in calculating worker and firm quality. We therefore follow Mendes et al. (2010) who use productivity as a measure of firm quality and education (share of high educated workers) as a measure of worker quality. More specifically, we calculate firm level productivity (total factor productivity, TFP) and correlate it with the level of education of employees. TFP is based on the Levinsohn and Petrin (2003) method, using the number of blue- and white-collar workers, raw material costs and capital stock. We use three different measures on the skill level of the employees: the mean level of education, the share of employees with at least three years of post-secondary education, and the share with at least an undergraduate university education. The results are seen in Table A11 in the Appendix. Our results are similar to the previous ones: increased openness tends to improve matching in comparative advantage industries.

5. Conclusion

Previous literature has found the effect of trade liberalization to differ between different types of workers. For instance, Frías et al. (2009) use linked firm–worker data from Mexico and find that increased openness increases wage inequality mainly through a wage premium to

[33] We have also experimented with additional estimations to control for the effect of outliers but which are not shown in the paper. These include excluding industries with a large change in tariffs over the 10 year period, and estimating robust regressions and quintile regressions which are alternative methods to deal with outliers.

[34] See also Eeckhout and Kircher (2011).

[35] One implication of this is that the AKM approach tends to bias estimated correlations toward zero. Lopes de Melo argues that this is one of the reasons that previous studies of labor market matching have had difficulty finding evidence of positive assortative matching. It is important to note that we find a positive correlation between worker and firm effects despite this possible bias.

[36] We regress firm effects on observed firm characteristics and a quadratic term of them. All of the quadratic terms are significantly negative, indicating that the relationship between firm effects and observed firm characteristics is non-linear. However, we find that this relationship is monotonically increasing for more than 99% of firms in our sample. Details about this result are available upon request.

workers in exporting firms. Krishna et al. (2014) use similar data from Brazil and do not find a wage premium in exporting firms. They do, however, find evidence of sorting of workers following a liberalization, where the share of high educated workers increase in exporting firms. Liu and Trefler (2011) also find evidence of increased mobility following increased openness. More specifically, they find that U.S. import of services from China and India increases the amount of job switching in the U.S. labor market.

Our paper relates to this literature and examines how increased globalization affects the matching between firms and workers. Using matched worker–firm data from Sweden, we find strong evidence that increased openness improves the matching process in industries with greater comparative advantage while having no significant effect on matching in industries with a weaker comparative advantage. These results are broadly consistent with the theoretical predictions of Davidson et al. (2008) and Davidson and Matusz (2012). These papers argue that the self-selection of heterogeneous firms into exporting will improve the efficiency of the matching process when trade costs fall and that increased import penetration may have an ambiguous impact on matching. Our empirical results suggest that globalization will generate a previously unnoticed pure gain to countries involved in trade: The increased access that domestic firms gain to world markets will lead to better matching in the labor market without increased import penetration causing a countervailing loss. Quantitatively, our baseline results imply that lower tariffs result in better worker–firm matching in more than 80% of the industries in our sample. For the 20 industries with the largest comparative advantage, matching improves on average by 1.15 standard deviations when tariffs fall by 1 standard deviation.

We have subjected our results to a wide variety of robustness checks. These results hold for alternative measures of our key variables and persist when we control for technical change at the industry level, domestic anti-competitive regulations and product market competition. They are also robust to the inclusion of match effects, and we have demonstrated that the results are not driven by outliers. Thus, our results appear to be quite robust.

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Appendix A

Table A1
Variable definitions.

Industry variables	
Matching correlation	Correlation between total firm and total person effects
MNE share of production	Share of MNEs in total production (sales)
Foreign tariffs	Tariffs on Swedish export by country of destination, weighted by Swedish export shares in 1995
Swedish tariffs	Swedish (EU) tariffs on products by country of origin, weighted by Swedish imports shares in 1995
ICT investments	Capital compensation for computing and communications equipment as a share of total capital compensation
R&D intensity	R&D expenditures in constant SEK
Growth in capital	Percentage growth in capital stock
Growth in capital intensity	Percentage growth in capital intensity

Table A1 (*continued*)

Firm variables	
Capital intensity	Net property, plant and equipment/employees (in million SEK)
Share of females	Number of women/employees
Firm size	Number of employees
Share high skilled	Number of workers with at least 3 years of post-secondary education/employees
Labor productivity	Value added/employees
Individual variables	
Wage	Monthly full-time equivalent salary, including wage, bonus, payment for overtime and work at unsocial hours
Experience	Age minus number of years of schooling minus seven
Education 1	1 if highest level of education is elementary school (<9 years), 0 otherwise
Education 2	1 if highest level of education is compulsory school (9 years), 0 otherwise
Education 3	1 if highest level of education is 2 years of upper secondary school, 0 otherwise
Education 4	1 if highest level of education is 3 years of upper secondary school, 0 otherwise
Education 5	1 if highest level of education is 4 years of upper secondary school, 0 otherwise
Education 6	1 if highest level of education is undergraduate or graduate college education, 0 otherwise
Education 7	1 if highest level of education is doctoral degree, 0 otherwise

Table A2
Descriptive statistics.

	Mean	Std dev	Observations
The degree of matching			
Firm effect and worker effect	−0.025	0.136	860
Firm effect and average worker effect	−0.074	0.553	860
Firm effect and median worker effect	−0.066	0.538	860
Unobserved firm effect and worker effect	−0.026	0.107	860
Capital intensity and worker schooling	0.000	0.131	860
Trade status			
Net exports/total trade	−0.037	0.383	860
Openness			
Foreign tariffs (%)	1.072	4.969	860
Swedish tariffs (%)	0.828	1.167	860
Multinational sales as a share of total sales	0.677	0.268	860
Controls for technical change			
ICT investments	0.210	0.215	860
R&D intensity	63,577	98,608	816
Growth in capital	0.100	0.637	860
Growth in capital intensity	0.317	1.112	860
Controls for domestic product market competition			
OECD regulatory impact indicator	0.057	0.010	860
Product market competition	8.828	2.390	769

Note: This table presents the summary statistics of the key variables used in the empirical analysis. All of the variables are measured at the industry-year level.

Table A3
Number of observations per person. Based on estimation on the period 1995–2005.

Obs. per pers.	Freq.	Percent	Cum.
1	466,007	22.28	22.28
2	298,793	14.28	36.56
3	237,687	11.36	47.92
4	195,895	9.36	57.29
5	175,474	8.39	65.68
6	148,201	7.08	72.76
7	122,099	5.84	78.60
8	105,038	5.02	83.62
9	107,184	5.12	88.74
10	123,388	5.90	94.64
11	112,119	5.36	100.00
Total	2,091,885	100.00	

Table A4
Number of movers per firm. Based on estimation on the period 1995–2005.

Movers per firm	Freq.	Percent	Cum.
0	309	3.52	3.52
1–5	1574	17.93	21.45
6–10	645	7.35	28.79
11–20	914	10.41	39.20
21–30	623	7.10	46.30
31–50	833	9.49	55.79
51–100	1122	12.78	68.56
>100	2760	31.44	100.00
Total	8780	100.00	

Table A5
Share of total movers.

Within comparative advantage industries	39%
Within comparative disadvantage industries	37%
From comp. adv. to comp. dis-adv.	13%
From comp. dis-adv. to comp. adv.	11%
3-digit level industries	
Within industries	58%
Between industries	42%

Note: Movers refer to workers who are employed in different firms in two subsequent years. Comparative advantage is based on a binary measure: an industry is defined as having a comparative advantage if this industry had a positive net export for 1995, and it is defined as having a comparative disadvantage if this industry had a negative net export for 1995. Movers within comparative advantage (disadvantage) industries include workers who change firms within comparative advantage (disadvantage) industries. Movers within (between) 3-digit level industries include workers who change firms within (between) industries without any distinction in comparative advantage and comparative disadvantage industries.

Table A6
Correlations between firm and worker attributes 1995–2005.

	Correlation coefficient between firm and worker unobservable effects	Correlation coefficient between firm and worker total effects
Whole sample	0.0655	0.1076
Subsamples		
Workers observed at least 2 periods	0.0477	0.1038
Workers observed at least 3 periods	0.0316	0.1017
Firms with at least 2 movers	0.0658	0.1082
Firms with at least 5 movers	0.0664	0.1095
Workers with at least 3 observations and firms with at least 5 movers	0.0318	0.1022
Preferred sample		
Workers with at least 2 observations and firms with at least 5 movers	0.0481	0.1047

Note: The whole sample consists of 9,452,970 observations, and the preferred subsample has 8,977,269 observations.

Table A7
Correlations between firm effects and various firm characteristics.

	Pearson correlation	Spearman rank correlation
Labor productivity	0.2132	0.2466
Firm size in terms of capital stock	0.1296	0.3617
Firm size in terms of employment	0.1121	0.3268
Capital intensity	0.1120	0.2223
R&D/sales (1995–2002)	0.1047	0.1909
Export/sales	0.2297	0.2457

Note: All of the correlations are significantly positive at the 1% level. The total firm effects are based on the estimates of Eq. (2). See Section 3.2 for more details.

Table A8
Industries with the largest absolute values of net exports as a share of total trade.

SNI	Industry description	Net exports/ Total trade
Panel A: Twenty industries with the largest positive value of net exports as a share of total trade		
131	Mining of iron ores	0.936
201	Sawmilling and planing of wood, impregnation of wood	0.870
211	Manufacture of pulp, paper and paperboard	0.860
203	Manufacture of builders' carpentry and joinery	0.765
322	Manufacture of television and radio transmitters	0.615
342	Manufacture of bodies (coachwork) for motor vehicles	0.540
341	Manufacture of motor vehicles	0.527
232	Manufacture of refined petroleum products	0.499
352	Manufacture of railway and tramway locomotives and rolling stock	0.491
281	Manufacture of structural metal products	0.410
244	Manufacture of pharmaceuticals, medicinal chemicals and botanical products	0.403
296	Manufacture of weapons and ammunition	0.390
212	Manufacture of articles of paper and paperboard	0.380
204	Manufacture of wooden containers	0.337
295	Manufacture of other special purpose machinery	0.326
286	Manufacture of cutlery, tools and general hardware	0.301
271	Manufacture of basic iron and steel and of ferro-alloys	0.283
292	Manufacture of other general purpose machinery	0.273
141	Quarrying of stone	0.270
273	Other first processing of iron and steel	0.257
Panel B: Twenty industries with the largest negative value of net exports as a share of total trade		
177	Manufacture of knitted and crocheted articles	−0.860
193	Manufacture of footwear	−0.834
362	Manufacture of jewelery and related articles	−0.825
182	Manufacture of other wearing apparel and accessories	−0.809
192	Manufacture of luggage, handbags and the like, saddlery and harness	−0.748
335	Manufacture of watches and clocks	−0.673
142	Quarrying of sand and clay	−0.625
153	Processing and preserving of fruit and vegetables	−0.615
300	Manufacture of office machinery and computers	−0.578
321	Manufacture of electronic valves and tubes and other electronic components	−0.569
156	Manufacture of grain mill products, starches and starch products	−0.470
233	Processing of nuclear fuel	−0.459
152	Processing and preserving of fish and fish products	−0.442
160	Manufacture of tobacco products	−0.434
316	Manufacture of electrical equipment n.e.c.	−0.424
365	Manufacture of games and toys	−0.403
245	Manufacture of soap and detergents, cleaning and polishing preparations	−0.388
315	Manufacture of lighting equipment and electric lamps	−0.354
174	Manufacture of made-up textile articles, except apparel	−0.348
154	Manufacture of vegetable and animal oils and fats	−0.347

Table A9
Openness and assortative matching: weighted regressions on bootstrapped correlation coefficients.

	Reference (OLS)	WLS	WLS
	(1)	(2)	(3)
Foreign tariffs	0.014***	0.009*	0.010**
	(0.003)	(0.005)	(0.005)
Comparative-advantage × foreign tariffs	0.035***	0.022**	0.023**
	(0.007)	(0.010)	(0.010)
Observations	860	860	860

Note: Column 1 reports the result of column 1 of Table 2 in the paper. Columns 2–3 report the results of weighted least regressions (WLS) where the weights are the inverse of variance of the estimated correlation coefficients based on bootstrapping. In column 3, the dependent variable is the mean of bootstrapped correlation coefficients. All of the regressions include industry and year fixed effects. Standard errors reported in parentheses are clustered by industry. ***p < 0.01, **p < 0.05, *p < 0.1.

Table A10
Openness and assortative matching: weighted regressions.

	OLS	WLS				
	Reference	# of workers	Sales	Capital stock	Export	Total trade
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign tariffs	0.014***	0.013***	0.017***	0.018***	0.026***	0.024***
	(0.003)	(0.003)	(0.005)	(0.004)	(0.008)	(0.007)
Comparative-advantage × foreign tariffs	0.035***	0.032***	0.041***	0.039***	0.048**	0.048***
	(0.007)	(0.008)	(0.014)	(0.009)	(0.023)	(0.018)
Observations	860	860	860	860	860	860

Note: Column 1 reports the result of column 1 of Table 2 in the paper. Columns 2–7 report the results of weighted least regressions (WLS) where the weights are the inverse of variance of measures of industry size, e.g., industry sales in column 3. All of the regressions include industry and year fixed effects. Standard errors reported in parentheses are clustered by industry. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A11
Openness and assortative matching: using TFP for firm quality and education for worker quality.

	TFP and the median level of education in the workforce	TFP and share of workers with at least an undergraduate degree	TFP and the share of workers with at least 3 years of university education
	(1)	(2)	(3)
Foreign tariffs	0.027**	0.031*	0.015
	(0.012)	(0.016)	(0.011)
Comparative-advantage × foreign tariffs	0.041^{+}	0.067**	0.041*
	(0.026)	(0.033)	(0.023)
Observations	847	847	833

Note: In this table we measure the degree of matching using the correlation between firm-level productivity (TFP estimated using the Levinsohn and Petrin (2003) method) and the level of education of employees within the firm. In columns 1–3 the skill level of the employees is respectively measured as the median level of education in the workforce, the share of workers with at least an undergraduate degree, and the share of workers with at least 3 years of university education. The variable "comparative-advantage" represents the trade status of an industry which is measured as the value of net exports as a share of total trade for 1995. The tariff data are transformed so that an increase in the independent variable *Foreign tariffs* represents more openness. All of the regressions include industry and year fixed effects. Standard errors reported in parentheses are clustered by industries. See Section 3 for more details about data and measurement. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. $^{+}$ A one-tailed test for a positive coefficient cannot be rejected (p-value of 0.94).

References

Abowd, J.M., Kramarz, F., Margolis, D.N., 1999. High wage workers and high wage firms. Econometrica 67 (2), 251–333.
Abowd, J.M., Creecy, R.H., Kramarz, F., 2002. Computing person and firm effects using linked longitudinal employer–employee data. Technical Paper 2002–06. U.S. Census Bureau.
Acemoglu, D., 1999. Changes in unemployment and wage inequality: an alternative theory and some evidence. Am. Econ. Rev. 89 (5), 1259–1278.
Albrecht, J., Vroman, S., 2002. A matching model with endogenous skill requirements. Int. Econ. Rev. 43 (1), 282–305.
Andrews, M., Schank, T., Upward, R., 2006. Practical fixed-effects estimation methods for the three-way error-components model. Stata J. 6 (4), 461–481.
Andrews, M., Gill, L., Schank, T., Upward, R., 2008. High wage workers and low wage firms: negative assortative matching or limited mobility bias? J. R. Stat. Soc. Ser. A 171 (3), 693–697.
Antràs, P., Garicano, L., Rossi-Hansberg, E., 2006. Offshoring in a knowledge economy. Q. J. Econ. 121 (1), 31–77.
Barth, E., Dale-Olsen, H., 2003. Assortative matching in the labour market? Stylised facts about workers and plants. Mimeo, Institute for Social Research, Oslo.
Becker, G., 1973. A theory of marriage: part I. J. Polit. Econ. 81 (4), 813–846.
Bernard, A., Redding, S., Schott, P., 2007. Comparative advantage and heterogeneous firms. Rev. Econ. Stud. 74 (1), 31–66.
Boone, J., 2008. A new way to measure competition. Econ. J. 118 (531), 1245–1261.
Boone, J., Van Ours, J., van der Wiel, H., 2007. How (not) to measure competition. TILEC Discussion Paper No. 2007-014.
Card, D., Heining, J., Kline, P., 2014. Workplace heterogeneity and the rise of West German wage inequality. Q. J. Econ. 128 (3), 967–1015.
Cornelissen, T., 2008. The Stata module felsdvreg to estimate a linear model with two high-dimensional fixed effects. Stata J. 8 (2), 170–189.
Cornelissen, T., Hubler, O., 2011. Unobserved individual and firm heterogeneity in wage and job-duration functions: evidence from German linked employer–employee data. Ger. Econ. Rev. 12 (4), 469–489.
Costinot, A., 2009. An elementary theory of comparative advantage. Econometrica 77 (4), 1165–1192.
Costinot, A., Vogel, J., 2010. Matching and inequality in the world economy. J. Polit. Econ. 118 (4), 747–786.
Davidson, C., Matusz, S., 2012. A model of globalization and firm–worker matching: how good is good enough? Int. Rev. Econ. Financ. 23, 5–15.
Davidson, C., Matusz, S., Shevchenko, A., 2008. Globalization and firm level adjustment with imperfect labor markets. J. Int. Econ. 75 (2), 295–309.
Davidson, C., Heyman, F., Matusz, S., Sjöholm, F., Zhu, S., 2012. Liberalized trade and worker–firm matching. Amer. Econ. Rev. Pap. Proc. 102 (3), 429–434.
Doms, M., Dunne, T., Troske, K., 1997. Wages, workers, and technology. Q. J. Econ. 112 (1), 252–290.
Eeckhout, J., Kircher, P., 2011. Identifying sorting — in theory. Rev. Econ. Stud. 78 (3), 872–906.
Frías, J., Kaplan, D., Verhoogen, E., 2009. Exports and Wage Premia: Evidence from Mexican Employer–Employee Data, Columbia University Working Paper.
Goldberg, P., Pavcnik, N., 2005. Short-term consequences of trade reform for industry employment and wages: survey evidence from Colombia. World Econ. 28 (7), 923–939.
Goux, D., Maurin, E., 1999. Persistence of inter-industry wage differentials: a reexamination using matched worker–firm panel data. J. Labor Econ. 17, 492–533.
Grossman, G., 2004. The distribution of talent and the pattern and consequences of international trade. J. Polit. Econ. 112, 209–239.
Grossman, G., Maggi, G., 2000. Diversity and trade. Am. Econ. Rev. 90, 1255–1275.
Gruetter, M., Lalive, R., 2004. The importance of firms in wage determination. IZA Discussion Paper No. 1367.
Haltiwanger, J., Kugler, A., Kugler, M., Micco, A., Pages, C., 2004. Effects of tariffs and real exchange rates on job reallocation: evidence from Latin America. J. Pol. Reform 7 (4), 191–208.
Hansen, C.B., 2007. Generalized least squares inference in panel and multilevel models with serial correlation and fixed effects. J. Econ. 140 (2), 670–694.
Hausman, J.A., Taylor, W.E., 1981. Panel data and unobservable individual effects. Econometrica 49 (6), 1377–1398.
Helpman, E., Krugman, P., 1985. Market structure and foreign trade: increasing returns, imperfect competition, and the international economy. The MIT Press, Cambridge, MA.
Helpman, E., Itskhoki, O., Redding, S., 2010. Inequality and unemployment in a global economy. Econometrica 78 (4), 1239–1283.
Kremer, M., Maskin, E., 2006. Globalization and Inequality, Harvard University Working Paper.
Krishna, P., Poole, J., Senses, M., 2014. Wage effects of trade reform with endogenous worker mobility. J. Int. Econ. 93 (2), 239–252.
Legros, P., Newman, A., 2002. Monotone matching in perfect and imperfect worlds. Rev. Econ. Stud. 69, 925–942.
Legros, P., Newman, A., 2007. Beauty is a beast, frog is a prince: assortative matching with non-transferabilities. Econometrica 75 (4), 1073–1102.
Levinsohn, J., 1999. Employment responses to international liberalization in Chile. J. Int. Econ. 47 (2), 321–344.
Levinsohn, J., Petrin, A., 2003. Estimating production functions using inputs to control for unobservables. Rev. Econ. Stud. 70 (2), 317–342.
Lise, J., Meghir, C., Robin, J., 2013. Mismatch, sorting and wage dynamics. NBER Working Paper No. 18719.
Liu, R., Trefler, D., 2011. A sorted tale of globalization: white collar jobs and the rise of service offshoring. NBER Working Paper 17559.
Lopes de Melo, R., 2009. Sorting in the labor market: theory and measurement. University of Chicago Working Paper.
Melitz, M., 2003. The impact of trade on intra-industry reallocations and aggregate industry productivity. Econometrica 71, 1695–1725.
Mendes, R., van den Berg, G.J., Lindeboom, M., 2010. An empirical assessment of assortative matching in the labor market. Labour Econ. 17, 919–929.
Menezes-Filho, N.A., Muendler, M., 2007. Labor reallocation in response to trade reform. University of California at San Diego Working Paper No. 251555.
Mortensen, D., Pissarides, C., 1994. Job creation and job destruction in the theory of unemployment. Rev. Econ. Stud. 61 (3), 397–415.
Ohnsorge, F., Trefler, D., 2007. Sorting it out: international trade with heterogeneous workers. J. Polit. Econ. 115 (5), 868–892.
Roy, A., 1951. Some thoughts on the distribution of earnings. Oxf. Econ. Pap. 3, 135–146.
Sattinger, M., 1993. Assignment models of the distribution of earnings. J. Econ. Lit. 31 (2), 831–880.
Shimer, R., Smith, L., 2000. Assortative matching and search. Econometrica 68 (2), 343–369.
Tinbergen, J., 1951. Some remarks on the distribution of labour incomes. In: Peacock, A., et al. (Eds.), International Economic Papers, No. 1. Macmillan, London, pp. 195–207.
Wacziarg, R., Wallack, J., 2004. Trade liberalization and intersectoral labor movements. J. Int. Econ. 64 (2), 411–469.
Woodcock, S., 2008a. Wage differentials in the presence of unobserved worker, firm, and match heterogeneity. Labour Econ. 15 (4), 771–793.
Woodcock, S., 2008b. Match effects. Available at SSRN: http://ssrn.com/abstract=931529.
Yeaple, S., 2005. A simple model of firm heterogeneity, international trade, and wages. J. Int. Econ. 65, 1–20.