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Abstract: This paper focuses on the ability of the labor market to correctly 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, or the trade status of an industry.

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Globalization and Imperfect Labor Market Sorting

A recent article in the *Quad-City Times* (based in Davenport, Iowa) chronicled how a variety of local residents have been forced to take less-than-ideal jobs to survive the recent recession.[1] The stories included those of a former mechanical engineer now employed as a truck driver, a computer programmer with 30 years of experience now working as a freelance writer, and a recent graduate with a degree in sports management working at Taco Bell. These workers do not show up in any of the labor statistics used to measure the performance of the economy – they are not unemployed, nor are they discouraged workers or part-time employees, so they would not be included in any measure of "underemployment" – but their predicaments are seen as sure signs that the economy is not operating efficiently. This article is not unique – it would be easy to find dozens of similar articles with a simple internet search. Many articles were present before the onset of the recession. At that point, they tended to focus on the role that globalization may play in destroying jobs and forcing workers to seek alternative employment (examples would include x-rays being sent to India to be read and technical call centers recently established in foreign countries). The concerns that are front and center in both types of articles are that the labor market may not be correctly assigning workers and their skills to tasks within the economy. This type of labor-market mismatch is difficult to measure and the factors that influence the degree of imperfect matching are not well understood. This paper focuses on the ability of the labor market to correctly match workers to jobs within a given industry and the role that globalization plays in that process.

The idea that workers with heterogeneous abilities could be mismatched with firms with heterogeneous skill requirements 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

[1] See "Underemployment keeps many Quad-Citians heads above water," in the *Local Business* section of the *Quad-Cities Times*, April 11, 2010.

[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.

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, Dunne and Troske 1997) and workers differ in education, physical attributes and raw 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 and conditions under which the market outcome yields the optimal pattern of sorting (e.g., Shimer and Smith 2000 and Legros and Newman 2002, 2007). For the labor market, positive assortative matching translates into the most productive firms employing the most highly skilled workers.

Davidson, Matusz, and Shevchenko (2008) provide insight into the effects that globalization might have on labor market mismatch. Their model, henceforth referenced as the DMS model, consists of a perfectly competitive industry populated by heterogeneous firms that differ in the sophistication of the technology that they use and heterogeneous workers differentiated by ability. High-ability workers are better suited for the jobs created by high-tech firms, so that positive assortative matching is optimal. However, the existence of labor market frictions implies that equilibrium sorting may be imperfect – that is, some high-ability workers may accept low-tech jobs if they happen to be matched with low-tech firms first and those firms can afford to offer a wage high enough to induce them to stop searching. As in any model of trade with heterogeneous firms, it is those firms that adopt the modern technology (the most productive firms) that have the greatest access to international markets. Changes in the degree of openness therefore have a disproportionate effect on the profitability of adopting the modern technology. As trade costs fall, the mix of firm types and the wage offers that they can afford to make are altered. The key predictions are that (a) in comparative-advantage industries greater openness leads to better labor market sorting[3] and (b) in comparative-disadvantage industries greater openness may increase the

[3] Helpman, Itskhoki and Redding (2010) derive similar results in that they show that greater openness amplifies differences in the workforce across firms. In particular, in their setting openness strengthens the correlation between

mismatch between workers and firms.[4] Both of the results are driven by how openness affects the relative revenues earned by high-tech and low-tech firms in perfectly competitive markets.

Our goal in this paper is to test these sharp predictions about openness and imperfect matching using matched worker-firm data from Sweden. We are mainly interested in how matching has changed over time, whether openness can explain this change, and whether the effect of openness differs between comparative-advantage and comparative-disadvantage industries. The data requirements to carry-out this exercise are demanding. We need extensive information about workers, firms, and their employment relationships over time. The Swedish data set is ideal for this, since it is both extensive, including roughly 50% of the workforce and all firms in Sweden with more than 20 employees, and rich in detail concerning worker characteristics, firm characteristics and employment relationships. 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, Gill, Schank and Upward 2008). We construct the 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, Kramarz and Margolis (1999) and the literature that has followed.

To identify the effect of openness on the degree of matching, we use different measures of openness. Our preferred measure of openness is tariffs. Reducing foreign tariffs imposed on Swedish exports increases market access for Swedish firms and widens the revenue gap between exporters and non-exporters, while a reduction in Swedish tariffs imposed on foreign imports may intensify import competition narrowing the gap.[5] The main advantage of using tariffs is that they can be considered as

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firm productivity and average worker ability. This is consistent with greater openness resulting in an increase in positive assortative matching.

[4] We use the terms "comparative-advantage industries" and "comparative-disadvantage industries" to be consistent with Bernard et al. (2007). Since the firms are assumed to be perfectly competitive, we could also refer to these as "export-oriented" and "import-competing" industries.

[5] A reduction in Swedish import tariffs also reduces production costs for producers who use imported intermediate goods. A reduction in Swedish import tariffs could reduce the profit gap between exporters and non-exporters if more productive firms (the exporters) use more imported intermediate inputs than less productive firms.

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.

Figure 1 gives us a first glance of the Swedish data. 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.B for more details about the measure), and openness is measured by foreign tariffs imposed on Swedish exports. Over the sample period, the degree of matching increased steadily while foreign tariffs were reduced. Therefore, the plot displays a strong positive correlation between openness and positive assortative matching. However, this positive correlation may reflect a spurious correlation rather than a causal effect of openness on the degree of matching. To identify the effect of openness on the degree of matching, we exploit the within-industry and over-time variation in the measures of openness and the degree of matching. In addition, the DMS model predicts that more openness increases the degree of matching for industries with greater comparative advantage. Thus, in the empirical analysis we also look at whether the effect of openness is systematically related to the trade status of an industry as predicted by the DMS model. Finally, to identify the effect of openness we also control for other industry-level time-varying factors that may affect the degree of matching. 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.

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 matching in the labor market. This result remains 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, or the trade status of an industry.

There are at least two reasons to focus on globalization's influence over labor market sorting. The first has to do with the aforementioned public perception that trade-induced job displacement results in significant losses for some highly-skilled workers by forcing them to accept less preferred jobs. However, our empirical results do not provide any support for this view. In fact, our results suggest that globalization creates a pure gain by improving the efficiency of matching in comparative-advantage industries without causing the matching process to deteriorate in comparative-disadvantage industries.

The second reason to focus on the link between imperfect matching and globalization has to do with the recent emphasis on firm heterogeneity for a variety of trade-related issues. Empirical findings generated over the past 15 years indicate that in comparative-advantage industries not all firms are engaged in exporting. Firms that export tend to be larger, more capital intensive and pay higher wages than their counterparts that sell all of their output domestically. In addition, globalization appears to magnify the degree of firm heterogeneity by reallocating market shares in favor of the highly productive firms.[6] This makes the strongest firms stronger and the weakest firms weaker. It is now widely accepted that firm heterogeneity within a given industry is an essential component of "new, new" trade models.

On the other side of the labor market it should be clear that there are significant differences across workers in terms of skills. For example, studies by Barro and Lee (1993, 1996, 2001) document the wide disparity of educational attainment within most countries. Grossman and Maggi (2000) use data on literacy scores within and across countries to make the same point. Thus, there is ample evidence that labor markets within narrowly defined industries are characterized by two-sided heterogeneity. In addition, the empirical literature on job creation and job destruction (e.g., Davis, Haltiwanger and Schuh 1996) suggests that the labor market does not always perfectly match workers to jobs as we observe considerable churning even within stable industries as workers and firms sever relationships in search of

[6] See Bernard, Jensen, Redding and Schott (2007) for an excellent survey of the work on heterogeneous firms and trade. Citations to the papers that have provided these stylized facts are included in the survey.

better matches. As we noted earlier, the factors that influence the degree of imperfect matching in the labor market are not yet well understood. This is particularly true with respect to the role of globalization.

Although there is now extensive research, both empirical and theoretical, that explores the implications of firm-level heterogeneity for international trade, the literature on worker heterogeneity and trade is far more limited and has grown more slowly. Grossman and Maggi (2000) was one of the earliest contributions. One of their main goals was to show that the distribution of talent could be a source of comparative advantage. Grossman and Maggi assume that all firms within a sector are identical, so they are focusing on the sorting of heterogeneous workers across sectors with different production processes. They also assume competitive markets so that matching is always efficient – thus, the type of labor-market mismatch that we are interested in studying cannot arise in their setting. These same features can be found in the other important papers on labor market sorting and trade, including Grossman (2004), Yeaple (2005), Antras, Garicano and Rossi-Hansberg (2006), Kremer and Maskin (2006), Ohnsorge and Trefler (2007), Costinot (2009) and Costinot and Vogel (2010) – most focus on sorting across industries and all assume competitive labor markets.[7] In contrast, we are interested in the impact of globalization on the *imperfect* sorting of heterogeneous workers across heterogeneous firms *within the same industry*.

In the next section, we provide a more detailed description of the DMS model and its predictions. We also compare the mechanism that drives the results in the DMS framework to a similar mechanism at work in Acemoglu (1999). In section 3 we describe the empirical approach that we take and discuss the data set and measurement issues. Our empirical results are presented in Section 4.

2. The Theory

To understand the forces that drive our predictions we begin by reviewing the insights on trade and matching from Davidson, Matusz and Shevchenko (2008). Their model, which is an open-economy extension of Albrecht and Vroman (2002), allows for heterogeneity on both sides of the labor market. On

[7] Yeaple (2005) is an exception here – he has heterogeneous workers sorting across two types of firms with the same industry. But, he assumes competitive labor markets so that sorting is optimal. The frameworks used by Costinot (2009) and Costinot and Vogel (2010) are also flexible enough that they could be used to study sorting within a sector – but, again, they assume competitive labor markets so that sorting would always be efficient.

the supply side, there are two types of workers: high-ability and low-ability. On the demand side, ex-ante identical perfectly competitive firms must adopt a technology when entering the market and, as in Yeaple (2005), incentives exist such that more than one technology is selected in equilibrium. This gives rise to firm-heterogeneity. There are two potential technologies that firms may use. Those that select the modern technology (high-tech firms) must recruit a high-ability worker in order to produce; whereas those that adopt the basic technology (low-tech firms) can produce using either type of worker. Each firm employs one worker and a variable amount of capital to produce its good. The productivity of a firm is tied to the ability of its worker with high-ability workers more productive than their low-ability counterparts. However, high ability workers are more costly to hire since they can command a higher wage. Thus, firms that adopt the modern technology will be more productive and earn more revenue, but they will also incur higher labor costs. Capital is rented in a spot market after the worker is hired. In contrast, frictions in the labor market force workers to search for jobs. Search is random, with workers negotiating their wages once hired so that, as in most search models, the equilibrium wage is given by the Nash Bargaining Solution. Since search is costly, firms and workers may end up mismatched in that a worker may find it optimal to accept a less than ideal job if the expected benefit from continuing to search for a better job is lower than the cost of additional search.

DMS make the usual assumptions with respect to entry in that all firms must pay a fixed cost to set-up production and incur an additional fixed cost to access world markets. The fixed cost of exporting implies that some firms may decide to sell all of their output domestically. Upon entry, each firm selects a technology and posts a vacancy. The proportion of firms that select the basic technology and the total mass of firms producing are determined by free entry conditions. We follow DMS and use γ to denote the proportion of vacancies that are unfilled and tied to low-tech firms. We are interested in equilibria of the DMS model in which $0 < \gamma < 1$ so that the market is characterized by both firm and worker heterogeneity. In addition, we focus on the case in which the model's parameters are such that high-ability workers are better matched when employed by high-tech firms. This implies that positive assortative matching is optimal – that is, high-ability workers should be matched with high-tech firms.

There are two types of equilibria in this model depending on whether high-ability workers are willing to accept low-tech jobs. If they are willing to do so, then we have a *Cross-Skill-Matching* equilibrium in which some high-ability workers are underemployed (or mismatched) in equilibrium – that is, there is imperfect sorting in the labor market. While these workers are better suited for high-tech employment, they accept low-tech jobs if they happen to match with low-tech firms first and if low-tech firms can afford to pay a wage high enough to induce these workers to stop searching. This can occur if the revenues earned by the two types of firms are sufficiently close to each other. In the other type of equilibrium, high-ability workers search until they find high-tech jobs. Such an *Ex-Post Segmentation* equilibrium exists if the revenues earned by the two types of firms are sufficiently different so that low-tech firms cannot afford to pay high ability workers enough to induce them to stop searching.

The model is summarized in Figure 2. Firms that enter pay the fixed cost of entry, select a technology and post a vacancy. Unemployed workers are then randomly matched with firms with vacancies. If the firm and the worker can agree on a wage, the firm rents capital and then production takes place. Production continues until the match breaks-up, which occurs at a constant rate. Once the job is destroyed, the partners reenter the search process. If the firm can increase profit by exporting some of its output, it pays the fixed cost of exporting and sells its goods on the world market at the world price of p^*. Alternatively, firms can sell some or all of their output in the domestic market where the price is p.

There are three types of firms that may be observed in equilibrium: high-tech firms matched with high-ability workers (type H); low-tech firms matched with low-ability workers (type L); and low-tech firms matched with high-ability workers. If we use M to denote the measure of the last type of firm, then $M > 0$ in a Cross-Skill Matching equilibrium and $M = 0$ in an Ex-Post Segmentation equilibrium. Firms enter until the expected profit from creating a high-tech vacancy or a low-tech vacancy are driven to zero; and, since both values are driven to zero, in equilibrium firms are indifferent about the type of vacancy they create. Low-ability workers are only offered low-tech jobs and they always accept them. High-ability workers accept a low-tech job if the wage offered exceeds their expected value from continuing to search for a high-tech job. One feature of the model that is worth highlighting concerns the wage structure. If we use w_i to denote the wage paid by a type i firm, we first note that $w_H > w_M$. This follows from the fact that high-ability workers are more productive when employed by high-tech firms. Second, since high-ability workers employed by low-tech firms have better outside opportunities than their low-ability counterparts, they can demand a higher wage from low-tech firms – thus, $w_M > w_L$.

As in other models with heterogeneous firms (e.g., Melitz 2003; Yeaple 2005; Bernard et al 2003) the most productive firm (in our case, high-tech firms) enjoy the strongest incentive to export while the least productive firms (in our case, low-tech firms matched with low-ability workers) have the weakest incentives to do so. The implication is that as trade costs fall, the most productive firms expand at the expense of the least productive firms – that is, market shares are reallocated in favor of high-tech firms. For our purposes, the main insights from DMS are that (1) openness affects relative revenues earned by the high-tech and low-tech firms and (2) the manner in which relative revenues are affected depends on the industry's trade position. In comparative-advantage markets, increasing openness makes it easier for all firms to sell their goods on world markets, where the world price exceeds the domestic price. And, since high-tech firms have greater incentive to export than low-tech firms and since they employ the most productive workers in the industry, openness increases the spread between the revenues earned by the types of firms. As a result, as markets become more open, low-tech firms will have a harder time attracting and retaining high-skilled workers. The implication is that if the economy begins in a Cross-Skill Matching equilibrium, increased openness can destroy it by making it impossible for low-tech firms to attract high-ability workers. Alternatively, if the economy remains in a Cross-Skill Matching equilibrium, the frequency with which workers and firms are mismatched declines as openness increases.

Tracing through the forces that drive these results provides insight into how the model works. As trade costs fall, type H firms take advantage by producing more and exporting a greater share of their output. This increases the surplus to be split between the type H firms and their workers, resulting in an increase in w_H. The increase in w_H implies that the outside opportunities for all high-ability workers have improved and this triggers an increase in w_M. The increase in w_M may be large enough that it makes it unprofitable for low-tech firms to hire these workers. If so, the Cross-Skill Matching equilibrium is destroyed. If the Cross-Skill Matching equilibrium remains intact, then the increase in w_M reduces the profits for low-tech firms, resulting in some exit. In addition, the fall in trade costs induces entry by high-tech firms. As a result, fewer high-ability workers wind up employed by low-tech firms.

To summarize, this model yields a rather sharp prediction about how match quality ought to be linked to openness in comparative-advantage industries. As markets become more open, more high-ability workers should be matched with high-tech firms, whereas a higher fraction of low-tech firms should be matched with low-ability workers. Thus, in comparative-advantage industries increased openness should lead to a more efficient allocation of talent. This could be viewed as a new (potentially important) gain from trade.[8]

The DMS predictions are reversed for comparative-disadvantage industries. In these industries, globalization leads to a reduction in the market price p, as new, lower-priced substitute goods are imported from world markets. This lowers the revenues earned by all domestic firms and shrinks the gap between the revenues earned by low-tech and high-tech firms, making it *easier* for low-tech firms to attract and retain highly-skilled workers. The implication is that if the economy begins in an Ex Post Segmentation equilibrium, increased openness can cause the economy to switch to a Cross-Skill Matching equilibrium as low-tech firms suddenly find that it is possible to attract high-ability workers. Alternatively, if the economy starts in a Cross-Skill Matching equilibrium, the frequency with which workers and firms are mismatched will increase as openness increases. As a result, greater openness ought to lead to an increase in the average quality of the workers hired by low-tech firms. Once again, we

[8] There are two caveats to this claim. First, it is important to remember that this assumes complementarities between worker skills and the sophistication of the technology used by firms. In such complementarities are absent, or if these attributes of the production process are actually substitutes, then other matching patterns might be more efficient. Second, even when such complementarities are present, the presence of search frictions will constrain the economy, keeping it from reaching the first-best outcome. And, we know from the literature on search theory that we should expect at least some worker/firm mismatch in the constrained efficient outcome. Thus, for our results to suggest that openness will lead to new gains from trade, it must be the case that the initial market-induced allocation of labor across firms is characterized by an inefficiently high degree of mismatch.

have a rather sharp prediction about the link between openness and the efficiency of the labor market: in comparative-disadvantage industries an increase in openness should lead to a less efficient allocation of talent in the labor market. This could be viewed as a new cost of globalization.

In terms of empirical work, one limitation of the DMS model is that the assumption of perfect competition in the product market is inconsistent with intra-industry trade. In reality, almost all industries are characterized by two-way trade. We would expect that increased openness due to (for example) a reduction in trade costs would result in more export opportunities as well as more intense import competition in any particular industry. The DMS model predicts that the increased export activity would result in better labor market sorting while the increase in import penetration would lead to less efficient sorting. One way to account for these two competing forces in our empirical work would be to use a continuous measure of trade status, one that measures the proportion of trade that is tied to export activity and also captures the pattern of comparative advantage. We introduce such a measure in Section 3 below.

We close this section with a brief discussion of Acemoglu (1999), the work that is most closely related to ours. Acemoglu presents a closed-economy model in which high-skilled and low-skilled workers search across (possibly) heterogeneous firms for jobs. He shows that two types of equilibria can exist. In the first, some firms create high-tech jobs and match only with high-skilled workers while other firms create low-tech jobs and match only with low-skilled workers. In the other equilibrium, all firms create the same type of jobs and match with both types of workers. Since all firms adopt the same strategy, this is a pooling equilibrium. Acemoglu refers to the jobs associated with the pooling equilibrium as "middling" and shows that middling jobs will be offered only when the relative productivity of high-skilled versus low-skilled workers is not too great; otherwise, equilibrium entails separation. Thus, skill-biased technical change, which widens the gap between the workers' productivities, can move the economy from a pooling equilibrium to a separating equilibrium.[9] When this happens, high-skilled workers gain and low-skilled workers are harmed. In the latter part of his paper,

[9] See Albrecht and Vroman (2002) for a similar argument.

Acemoglu offers a variety of evidence that in many industries middling jobs have been disappearing and have been replaced by the type of jobs that would be offered in a separating equilibrium.[10]

If we apply the logic presented in this paper to Acemoglu's model, the conclusion is that openness should cause middling jobs to *disappear* in comparative-advantage industries and *appear* in comparative-disadvantage industries. This follows from the fact that exporting increases the spread between the revenues that the two types of workers can generate, just like skill-biased technical change in Acemoglu's framework, while import competition decreases this spread. In his empirical analysis, Acemoglu does not separate his industries into groups based on their trade status. Our model suggests that doing so might allow for a direct test of our model's prediction that openness can alter the nature of the labor-market equilibrium. That is the issue that we take up in the next two sections of this paper.

3. Empirical Specification, Data and Measurement

To examine our theoretical predictions, we use the following specification:

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

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 measurement.

The year fixed effects control for the 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

[10] Thus, Acemoglu's work provides a theoretical explanation of the polarization of the labor market that has recently been documented for the US, UK and Europe by Autor, Katz and Kearney (2006), Goos and Manning (2007) and Goos, Manning and Salomons (2009), respectively.

on within-industry over-time variation in the degree of matching and openness. The DMS model predicts that more openness increases the degree of matching for industries with greater comparative advantage. To test this prediction, we include an interaction between openness and the trade status of an industry in (1). 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.

A. 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.[11] 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 dataset covers more than two million individuals (accounting for roughly 50% of the labor force) and includes information on workers education, occupation, sector, and demographics. The plant-level data add establishment information on the composition of the labor force with respect to educational level and demographics.[12]

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, the wage bill, value added, profits, sales, a foreign ownership dummy, multinational status, and industry affiliation. See Table A1 in the appendix for a description of the variables.

B. 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 capital intensity and high-skilled workers can be characterized as those with more years of education.

[11] 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.

[12] The plant-level data are aggregated to the firm level. In the following, we only use 'firms.'

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. The quality of firms and workers should include both observed and unobserved aspects. Thus, unlike the previous literature on assortative matching, our benchmark measure is based on both observed and unobserved worker and 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. 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 literature.[13]

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

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

where $logw_{ht}$ 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. Equation (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.[14] Time-varying worker characteristics include experience squared, higher-degree polynomials of experience, and a dummy variable for blue-collar occupations.[15] Since education is time invariant, it is subsumed in the worker fixed effects. Time-varying

[13] 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.

[14] The wages for workers who take a maternity/paternity leave are reported as the same as prior to their leave.

[15] In our sample 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 equation (2).

firm characteristics include capital intensity, firm size (number of employees), labor productivity (value added per worker), share of high-skill workers (i.e., share of the labor force with at least 3 years of post-secondary education), manufacturing indicator, share of female workers and its interaction with the manufacturing indicator.[16]

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, 2006; Andrews el 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 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 percent of the firms have no movers (see Table A4 in the Appendix). More information on movers is given in Table A5 in the Appendix where movers are shown within and between industries categorized as comparative advantage/dis-advantage industries as discussed below. Most workers are moving within industries: around 76 percent. Moreover,

[16] We also ran wage regressions by excluding 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 specifications.

[17] The abbreviation stands for Fixed Effect for individual i combined with LSDV for firm j. We use the program felsdvreg (see Cornelissen 2006), which is a memory saving algorithm to estimate FEiLSDVj in Stata.

looking at the figures at different levels of industry classification, it is seen that the share of movers within industries declines with more detailed industry classifications but account for a majority of total movers even at a 3-digit industry level.

The mobility is high compared to many previous studies and brings the advantage of getting all firms, except the 3 percent 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 8,465 unique firms. The group of firms with no movers only consists of 1,917 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, 2006; Cornelissen and Hubler 2007). In addition, the high level of mobility in the Swedish data allows us to avoid limited mobility bias, which tends to lead to zero or negative correlation coefficients (see Andrews, Gill, Schank and Upward 2008). We follow Cornelissen and Hubler (2007) and only include workers that are observed in at least two periods and firms that have at least five movers.

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 equation (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, firms with higher productivity and a higher share of skilled workers pay higher wages. However, in contrast to column 1, the estimated coefficient on capital intensity turns negative after controlling for firm effects. The capital intensity variable only picks up variation within each firm over time since we have firm fixed effects. Because employment is easier to adjust than capital, one possible explanation for the negative coefficient on capital intensity is that firms shed workers and restrain wages when hit by a negative shock. In this case, higher capital intensity is associated with lower wages. 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. Overall, the results in column 2 seem reasonable.

Based on the estimates of equation (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 good 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 2007). 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 el 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.

C. 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 good producers, but may also reduce the production cost for importers of intermediate inputs. 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 of 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 outsourcing and 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 percent 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.

D. 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

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

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 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 planning 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 would 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 would dominate, leading to a positive relationship between increased market access and the degree of matching. On the other hand, for industries with 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 would dominate, resulting 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

[19] One version of the Grubel-Lloyd index of intra-industry trade is 1− |exports − imports|/(exports + imports).
[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 less than 0.0001.

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 – 90% of the industries have consistent definitions of trade status based on these measures.

4. Empirical Results on Openness and Matching

A. Baseline estimates

Table 2 reports the estimation results for equation (1). Our baseline estimates include only foreign tariffs as the measure of openness because as will be shown below, reduced Swedish tariffs have opposing effects on the degree of matching and thus generate insignificant estimates for the effect of Swedish tariffs. Note that in Table 2 the tariff data are transformed so that an increase in the independent variable *Foreign Tariffs* represents more openness. To account for possible serial correlations within industries, standard errors are clustered at the 3-digit SNI industry level.

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 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 the 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 of reduction in foreign tariffs (i.e., 5%) can increase the degree of matching in the industry of mining iron ores 1.72 times of the standard deviation.[21]

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 56% of the standard deviation. (The computation is similar to footnote 21.)

These results provide strong support for the DMS model. 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 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. This 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

[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 $(0.0144+0.0347\times0.936)\times5 = 0.234$, which is 1.72 times of 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.

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.

We also divide the sample into comparative advantage and comparative dis-advantage industries based on positive and negative net export 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.

B. 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. On the one hand, reduced Swedish tariffs on foreign imports may intensify import competition to Swedish producers of the goods that directly compete with foreign imports. High-tech firms would suffer more from import competition because revenue losses are bigger for high-tech firms than for low-tech firms. In this case, low-tech firms may be able to offer more skilled workers a wage high enough to induce them to stop searching for higher wage jobs. As a result, there is more mismatch between firms and workers. On the other hand, lower Swedish tariffs may reduce the cost of intermediate inputs, spreading the surplus between high-tech and low-tech firms, since the former are larger and therefore use more intermediates than the latter. As a result, it will make it harder for low-tech firms to attract more skilled workers, and the degree of assortative matching improves. Since our industry-level analysis pools both types of producers, we cannot distinguish the different impact of reduced Swedish tariffs on different types of producers within an industry. Therefore, we find insignificant estimates for Swedish tariffs and include only foreign tariffs as the measure of openness in the baseline results.

In column 3 we measure openness using the share of sales by multinational firms. 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 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.[22] 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.

C. Accounting for match effects

The Abowd-Kramarz-Margolis type wage regression can be generalized 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 and can be interpreted as rent sharing between workers and firms. Woodcock (2008a, 2008b) argues 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 fixed effect method, and the other is the hybrid mixed random effect method. The orthogonal fixed 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 random effect method treats worker, firm and match effects as random, but allow arbitrary correlation between the random effects and time-varying observable characteristics.

[22] 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.

This differs from an ordinary random effects model that would impose restrictions on the relationship between observables and unobservables. The hybrid mixed random effect approach is again first to estimate the return to observables using the within-spell estimator. It then decomposes the wage residual into person, firm, and match effects under the random effects assumption, i.e., allowing the observables and the random effects to be correlated. The identification is based on moment restrictions on the random effects, which is similar to the Hausman and Taylor (1981) correlated random effects estimator.

We estimate the wage equation (1) by adding match effects and then construct the measure of the degree of matching as the correlation coefficient between worker and firm total effects. Columns 2-5 of Table 4 report the results when these alternative measures of the degree of matching are used. 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 allow 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 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.

D. Technical Change

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-skill and low-skill workers; and, as a result, the degree of positive assortative matching rises. However, since their models do not allow for trade, an industry's trade status plays no role in their analyses. 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. It is well known that skill-biased technical change is hard to measure. In the literature the share of investment in computing and communication equipment, and R&D expenditures per employee are often used as proxies for technical change. Under the assumption of capital-skill complementarity, capital deepening can raise the demand for skilled workers and may increase the degree of positive assortative matching. To capture this aspect, we also include annual growth rate in capital stock and annual growth rate in capital intensity as additional controls. As shown in Table 5, none of the measures have any significant impact on the degree of matching. On the other hand, our estimates of the effect of openness remain unchanged.

E. Domestic anti-competitive deregulations and product market competition

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 6.

The regulatory indicator captures the amount of anti-competitive regulations at the two-digit industry level and is constructed by the OECD. A higher value of the index indicates a higher degree of regulations.[23] Column 1 of Table 6 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.

[23] 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.

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.[24] The higher the absolute value of this elasticity, the fiercer is competition. The results reported in columns 2-3 of Table 6 indicate that this measure has no significant effect on the degree of matching. Again, our results for the effect of openness are unchanged.

F. 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 7. 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 if this industry had negative net exports in 1995. 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.[25] Therefore, these results are consistent with those reported in column 1 of Table 2 when the continuous measure of the trade status is used.

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[24] 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.

[25] 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-

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 that 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 7.

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.

Overall, Table 7 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.

G. 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 8). 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.

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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 $(0.014 - 0.035 \times 0.860)/2 = -0.008$.

H. 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 deMelo (2009), which focuses on the AKM approach's ability to correctly rank firms in terms of productivity.[26] 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 and 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.[27] 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 do more R&D activities. 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.[28] 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

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

[27] 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.

[28] 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 nonlinear. 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.

are significantly and positively correlated with our firm quality measure, strongly suggesting that the ranking we are getting from AKM seems to make sense.

6. Conclusion

This is one of the first empirical papers to investigate the impact of globalization on the efficiency of matching between heterogeneous firms and heterogeneous workers within industries.[29] 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 weaker comparative advantage. These results are broadly consistent with the theoretical predictions of Davidson, Matusz and Shevchenko (2008) and Davidson and Matusz (2010). 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.

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.

[29] There is some recent empirical work using matched employer-employee data to look at labor market effects of trade, particularly the impact of trade on wages and income distribution. For example, see Frías, Kaplan, and Verhoogen (2009), Krishna, Poole, and Senses (2011) and Helpman, Itskhoki, Muendler and Redding (2012).

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Figure 1 Assortative matching and openness

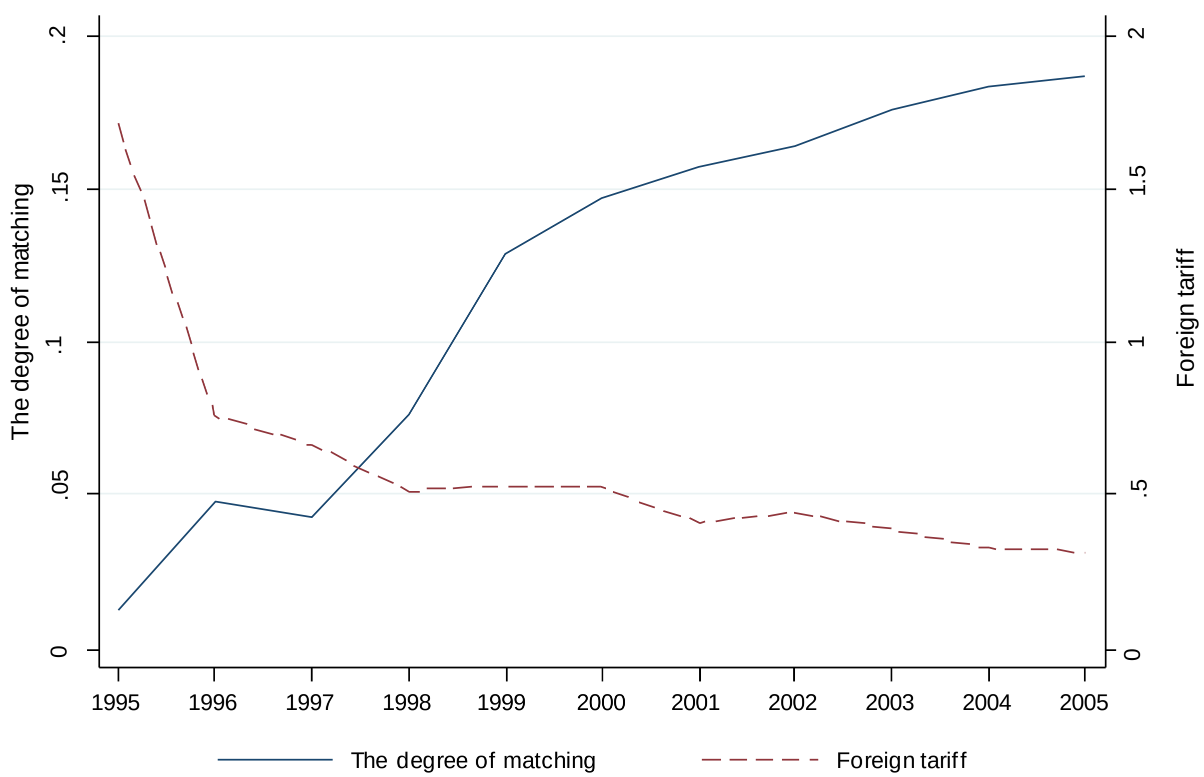

Figure 2. The Basic DMS Framework. How do changes in openness affect M?

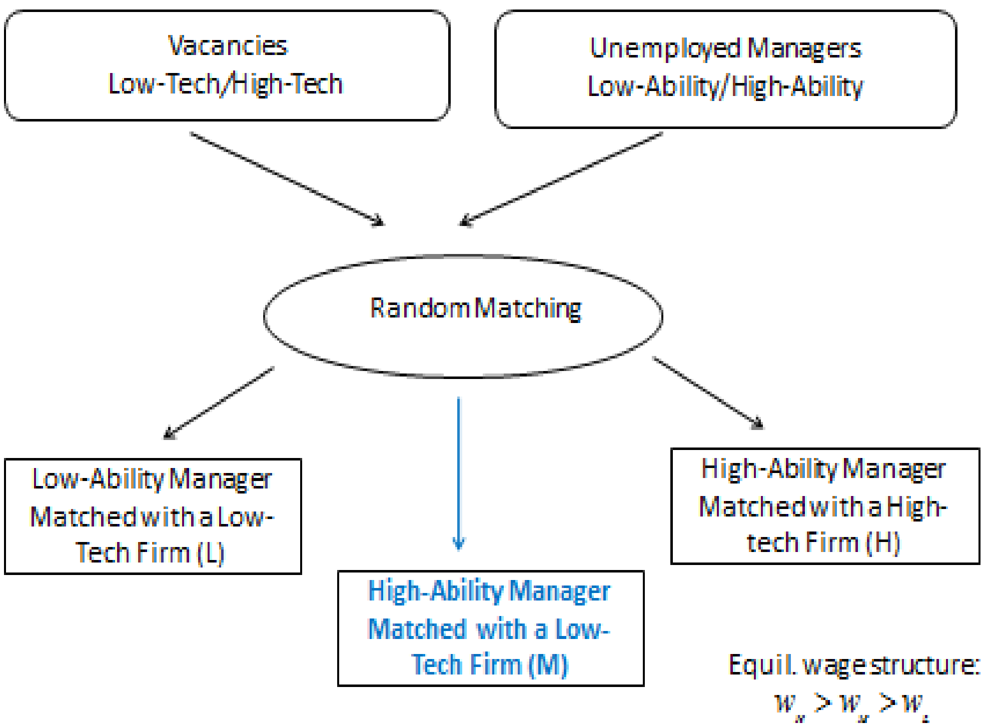

Table 1 Individual Worker Wage Regressions 1995-2005

	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)
Expereience^4/10000	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	0.0494***	-0.0028***
	(0.0002)	(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 equation (2). See Section 3.B for more details about the estimation. *** p<0.01

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
	(1)	(2)	(3)	(4)
Foreign tariffs	0.0144***	0.0416***	0.0469***	0.00724**
	(0.00295)	(0.0122)	(0.0105)	(0.00282)
Comparative-advantage × Foreign tariffs	0.0347***	0.118***	0.127***	0.0152**
	(0.00732)	(0.0265)	(0.0219)	(0.00708)
R^2	0.065	0.043	0.037	0.048

Notes: The dependent variable is the degree of matching. It is measured as the correlation coefficient between firm total effects and worker total effects in column 1, 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

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

Table 4 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

Notes: The dependent variable is the degree of matching. See Section 4.C 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

Table 5 Controlling for technical change at the industry level

	(1)	(2)	(3)	(4)	(5)
Foreign tariffs	0.0144***	0.0140***	0.0144***	0.0141***	0.0138***
	(0.00296)	(0.00288)	(0.00295)	(0.00294)	(0.00289)
Comparative-advantage × Foreign tariffs	0.0347***	0.0342***	0.0347***	0.0345***	0.0342***
	(0.00734)	(0.00721)	(0.00732)	(0.00725)	(0.00720)
ICT investments	-0.0144				-0.023
	(0.0335)				(0.034)
R&D intensity		0.0003			0.0003
		(0.0002)			(0.0002)
Growth in capital			0.002		-0.0004
			(0.004)		(0.003)
Growth in capital intensity				0.006	0.006
				(0.004)	(0.005)
R^2	0.065	0.078	0.065	0.067	0.080
Observations	860	816	855	855	816
Number of industries	88	84	88	88	84

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. Growth 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

Table 6 Controlling for domestic deregulations and product market competition

	(1)	(2)	(3)
Foreign tariffs	0.0120***	0.0128***	0.0109***
	(0.00268)	(0.00234)	(0.00202)
Comparative-advantage × Foreign tariffs	0.0307***	0.0310***	0.0273***
	(0.00687)	(0.00596)	(0.00545)
Regulatory Impact Indicator	10.90**		11.12*
	(5.344)		(6.580)
Product Market Competition		0.00351	0.00341
		(0.00273)	(0.00271)
R^2	0.080	0.080	0.092
Observations	860	769	769
Number of industries	88	77	77

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 7 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 × 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 × 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 × Swedish tariffs		0.0170		0.0112		0.0110
		(0.0233)		(0.0226)		(0.0228)
Comparative-advantage × 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 has positive net export for 1995, and it is defined as having a comparative disadvantage if this industry has negative net export for 1995. In columns 3-4 an industry is defined as having a comparative advantage if this industry has 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 has 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 8 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 industry × 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 industry × 1 year lagged foreign tariffs		0.0455***		0.0303*		0.0375**
		(0.00763)		(0.0182)		(0.0184)
Observations	857	764	847	755	860	766
R-squared	0.058	0.091	0.05	0.053	0.067	0.075
Number of observations	88	87	86	85	88	87

Notes: 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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix

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
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 high skilled 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	63577	98608	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

Table A3 Number of observations per person. Based on estimations 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 estimations on the period 1995-2005.

Movers per firm	Freq.	Percent	Cum.
0	309	3.52	3.52
1- 5	1,574	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	1,122	12.78	68.56
>100	2,760	31.44	100.00
Total	8,780	100.00	

Table A5 Share of total movers

Within comparative advantage industries	39%
Within comparative dis-advantage industries	37%
From comp. adv. to comp. dis-adv.	13%
From comp. dis-adv. to comp. adv.	11%
1-digit level industries	
Within industries	83%
Between industries	17%
2-digit level inudstreis	
Within industries	65%
Between industries	35%
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.

Table A6 Correlations Between Firm and Worker Attributes 1995-1995

	Correlation coefficient between firm and worker unobservable effects	Correlation coefficient between firm and workers 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 equation (2). See Section 3.B for more detail.

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 planning 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 jewellery 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