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Globalization and Imperfect Labor Market Sorting

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Abstract: This paper focuses on the ability of the labor market to 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 export-oriented industries. 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. On the other hand, we find no evidence that openness affects the degree of matching in import-competing industries. 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. In addition, we find no evidence that technical change has any impact on the degree of matching at the industry level. 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 wide-variety of local residents have been forced to take less-than-ideal jobs to survive the current recession.[1] The stories included: 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 of the measures of "underemployment" – but their predicaments are 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 even before the onset of the recession. At that point, they tended to focus on the role that globalization may play in destroying high tech jobs and forcing highly skilled workers to seek alternative employment (examples would often 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

[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.

physical capital, intelligence, education, wealth and physical characteristics and it unclear how these men ought to be matched with similarly heterogeneous women. Becker argued that under reasonable assumptions about the household production function that 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 workers they employ, 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 labor market sorting (see, for example, Shimer and Smith 2000 and Legros and Newman 2002, 2007). In the context of 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

Assignment models focus on firms that hire multiple workers and then must assign those workers to a variety of tasks.

key predictions are that (a) in export-oriented industries greater openness leads to better labor market sorting and (b) in import competing industries greater openness may increase the mismatch between workers and firms. Both of the results are driven by how openness affects the relative revenues earned by high-tech and low-tech firms.

Our goal in this paper is to test these sharp predictions about openness and imperfect matching using matched worker-firm data from Sweden. 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. Reduction in foreign tariffs imposed on Swedish exports can increase the market access for Swedish firms, while reduction in Swedish tariffs imposed on foreign imports may intensify import competition. 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 any substantial impact on the level of tariffs set by the EU. In addition, foreign tariffs are not affected by conditions in the Swedish industry. 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 export-oriented and import-competing industries.

Figure 1 gives us a first glance of the Swedish data. In both plots, the degree of matching is measured by the correlation between worker and firm total effects (including both observed and unobserved attributes). In panel A, openness is measured by foreign tariffs imposed on Swedish exports. In panel B, openness is measured by the share of multinational sales. Over the sample period, the degree of matching increased steadily. At the same time, foreign tariffs were reduced and the share of multinational sales increased. Therefore, both plots display 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 cross-industry and over-time variation in the measures of openness and the degree of matching. Another source of identification is based on the unique prediction of the DMS model that the effect of openness differs between export-oriented and import-competing industries. 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 positive assortative matching, we add industry-level controls for those factors.

We find strong evidence that openness improves the matching between workers and firms in export-oriented industries. 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. On the other hand, we find no evidence that openness affects the degree of matching in import-competing industries. 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. In addition, we find no evidence that technical change has any impact on the degree of matching at the industry level. 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 perception. In fact, our results suggest that globalization creates a pure gain by improving the efficiency of matching in export-oriented industries without causing the matching process to deteriorate in import-competing 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 export-oriented 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 exacerbate the degree of firm heterogeneity by reallocating market shares in favor of the highly productive firms that export.[3] This makes the strongest firms even stronger and the weakest firms even 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 severe relationships in search of

[3] 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 mismatching 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-Hansburg (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.[4] In contrast, we are interested in the affect of globalization on the *imperfect* sorting of heterogeneous workers across heterogeneous firms *within the same industry*. As far as we know, Davidson, Matusz and Shevchenko (2008) is the only theoretical paper that focuses on imperfect matching and trade. Moreover, this paper offers the first empirical evidence on the role that globalization plays in matching workers and firms within an industry.

In the next section, we provide a more detailed description of the DMS model and its predictions. We then describe one key theoretical extension designed to bridge the gap between the theory and the empirical work. 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.

[4] 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.

2. The Theory

To understand the forces that drive our theoretical predictions we begin by reviewing the insights on trade and assortative matching from Davidson, Matusz and Shevchnko (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 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 a high-ability or a low-ability worker. Each firm employs a single 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 and the rental rate is normalized to one. In contrast, frictions in the labor market 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. This outcome is unique to DMS since this is the only trade paper that has imperfect matching.

DMS make the usual assumptions with respect to entry in that all firms must pay a fixed cost of f to set-up production and incur an additional fixed cost of f_x 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 then posts a vacancy in order to hire a worker. 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 in the steady state equilibrium. The value of γ summarizes what we need to know about the mix of open jobs at any point in time and it is determined by free entry and steady state conditions. 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 parameters of the model 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, we prefer to have high-ability workers 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 what Albrecht and Vroman (2002) call a Cross-Skill-Matching (CSM) 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. This type of equilibrium, which Albrecht and Vroman refer to as 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 a wage high 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 production takes place. Production continues until the match breaks-up, which occurs at a constant rate. Once the job is destroyed, the partners start searching again for a new match. 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 export 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 two 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 output and exporting a greater share of their production. This increases the surplus to be split between the high-tech 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 expected profits for low-tech firms resulting in some exit by these firms. In addition, the fall in trade costs induces entry by new high-tech firms. As a result of the market's restructuring, 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 export-oriented markets. As markets become more open, high-ability workers should be more likely to match with high-tech firms, whereas a higher fraction of low-tech firms should be matched with low-ability workers. Thus, in export markets an increase in openness should lead to a more efficient allocation of talent in the labor market. This could be viewed as a new (potentially important) gain from trade.

The DMS predictions are reversed for import-competing 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 have a rather sharp prediction about the link between openness and the efficiency of the labor market: in import-competing 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 order to test these predictions, there are some limitations of the DMS model that need to be considered. To begin with, the assumption of perfect competition in the product market is inconsistent with intra-industry trade. In reality, 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 model can be extended to allow for intra-industry trade by assuming that the product market is characterized by monopolistic competition. The extension is straight-forward (see Davidson and Matusz 2010), and it leads to a small, but significant new insight. As trade costs fall, exporting increases and it is still the most productive firms that gain the most – as a result, the gap between the revenues earned by the high-tech and low-tech firms still rise so that, eventually, the low-tech firms will find it impossible to attract high-ability workers. In other words, as trade costs fall, the impact of greater domestic export activity leads to better matching. This is the same prediction generated by the perfectly competitive framework.

However, the reduction in trade costs also leads to greater import penetration and it is here that the insights from the perfectly competitive model become a bit muddled. To see this, note that under perfect competition all output produced domestically is sold in the home market. As import penetration drives down the domestic price, the gap between the revenues earned by the low-and high tech firms shrinks because the revenue gap is tied directly to the difference in their production levels ($q_H - q_L$ where q_i is the output of a typical type i firm). This is not the case under monopolistic competition, since even in import-competing industries the best firms will typically export only a fraction of their output. Under monopolistic competition, the gap in the revenues earned by the two types of firms is tied to the difference between the output levels offered for sale in the domestic market by the two types of firms – while high-tech firms produce more output, they sell a smaller fraction of their output in the domestic market. Thus, as trade costs fall, the impact of increased import competition on the quality of matching is unclear. This difference in the predictions of the two models is important, because, as we will see in Section 4, our empirical results do not support the DMS hypothesis that increased openness leads to less efficient matching in import-competing industries.

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. This separating equilibrium is quite is similar to the EPS equilibrium in our model. 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 as 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 separating equilibrium to a pooling equilibrium.[5] When this happens, high-skilled workers gain and low-skilled workers are harmed. In the latter part of his paper, Acemoglu offers a variety of evidence that in

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

many industries middling jobs have been disappearing and have been replaced by the type of jobs that would be offered in a separating equilibrium.[6]

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 export-oriented industries and *appear* in import-competing 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

The DMS model predicts that openness improves matching in export-oriented industries, but may reduce the degree of positive assortative matching in *import-competing* industries. To examine these theoretical predictions, we use the following specification:

$$Matching_{gt} = \alpha_0 + \alpha_1 Openness_{gt} + \alpha_2 Export\_oriented_g \cdot Openness_{gt} + D_t + D_g + \mu_{gt} \qquad (1)$$

where g indexes industries; t indexes years; $Matching_{gt}$ represents the degree of matching between workers and firms; $Openness_{gt}$ measures the degree of openness; $Export\_oriented_g$ is a dummy variable equal to one if industry g is export oriented, zero otherwise;[7] D_t and D_g represent year and industry fixed effects; and μ_{gt} is the error term that includes all of the unobserved factors that may affect the degree of matching. The year fixed effects control for the omitted macroeconomic factors that may

[6] 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.
[7] Details about the measurement of the degree of matching, openness, and the trade status of an industry will be given in the section on data and measurement.

affect the degree of matching. The industry fixed effects may capture the cross-industry difference in the degree of matching as a result of differences in production technology across industries. Because specification (1) controls for both year and industry fixed effects, identification of the openness effect on matching relies on cross-industry and over-time variation in the degree of matching and openness. The additional source of identification comes from α_2 which indicates the difference in the effect of openness between export-oriented and import-competing industries. The DMS model predicts that α_2 should be significantly positive. This sharp prediction about how the effect of openness should vary systematically across industries by trade status can 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 export-oriented and import-competing industries.

Our main coefficients of interest are α_1 and α_2. The effect of openness on the degree of matching for import-competing industries is captured by α_1, and the effect of openness for export-oriented industries is captured by $\alpha_1 + \alpha_2$. If the effect of openness is negative for import-competing industries, but positive for export-oriented industries, we expect that α_1 is significantly negative, and $\alpha_1 + \alpha_2$ is significantly positive.

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.[8] 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

[8] 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.

experience, 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.[9]

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

Measuring the degree of matching between workers and firms is a daunting task. Although the matched employee-employer dataset contains rich information about workers and firms, both workers and firms still have unobserved attributes that may have an impact on the degree of matching. 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, we measure the degree of matching based on both observed and unobserved worker and firm attributes. The other important deviation from the literature is that we construct the measure for each industry and each year.

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

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

where $\ln w_{ht}$ is the log wage of worker *h* at time *t*, $j(h,t)$ is worker *h*'s employer at time *t*, x_{ht} is a vector of observable time-varying worker characteristics, θ_h is the worker fixed effect, $Z_{j(h,t),t}$ is a vector of observable time-varying firm characteristics, $\phi_{J(h,t)}$ is the firm fixed effect, δ_t is the year fixed effect,

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

and v_{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.[10] Time-varying worker characteristics include experience squared, higher-degree polynomials of experience, and a dummy variable for blue-collar occupations.[11] Since education is time invariant, it is subsumed in the worker fixed effects. Time-varying 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. Note that the omission of observed firm attributes or unobserved firm effects from the wage regression can cause omitted variable bias in the estimation of the returns to worker abilities.

There are several estimation issues surrounding specification (2). Our Swedish data for 1995-2005 consist of around 10 million individual-year observations. Computer memory restraints preclude using the least-square dummy variable (LSDV) approach to estimate 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

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

[11] 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).

as FEiLSDVj[12] 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 in our sample is four (see Table A3 in the Appendix). Almost one third of our firms have more than 51 movers; the median value of movers is above 30; and only 3 percent of the firms have no movers (see Table A4 in the Appendix). This 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 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 wage premiums.

[12] 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.

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 the result in 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. Since employment is easier to adjust than the capital stock, one possible explanation for the negative coefficient on capital intensity is that firms shed workers and restrain wages when hit by a bad 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 of the wage regression 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 $Z_{j(h,t)}\lambda + \phi_{j(h,t)}$) are considered as good firms. Table 2 reports the correlation between firm and person effects. In order to compare our estimates with the prior literature, we also calculate the correlation only between unobserved firm and worker effects (θ_h and $\phi_{J(h,t)}$). The estimated correlation of unobserved effects ranges between 0.03 and 0.06 depending on specification. This positive correlation is in contrast with the surprising 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.

Our main interest is the correlation between both observable and unobservable firm and worker characteristics ($Z_{j(h,t)}\lambda + \phi_{j(h,t)}$ and $x_{ht}\eta + \theta_h$). As shown in Table 2, the correlation coefficients computed based on both observed and unobserved attributes are relatively large, mostly around 0.10. Again, we have positive assortative matching when workers with high skills tend to work in relatively good firms.

As mentioned above, the results might be biased if there are few observations per worker or few movers per firm. We therefore make several robustness estimations where we include different samples of firms and workers. Restricting our sample to workers with more observations reduces the correlation coefficient for unobservable characteristics: from 0.066 in the whole sample, to 0.048 when each worker has to be observed at least two periods, and to 0.032 when they have to be observed for at least 3 periods. The decline in the coefficient is relatively large but does not alter the qualitative results of positive assortative matching. The same pattern is not found for the correlation coefficient of both unobservable and observable characteristics: the coefficient shows a marginal decline from 0.108 for the whole sample to 0.104 when each worker is observed at least two periods; and to 0.102 when workers are observed at least three periods.

The results are robust to the exclusion of firms with few movers. In particular, for the correlation coefficient based on both observable and unobservable characteristics, it rises from 0.108 for the whole sample to 0.110 when firms with below five movers are excluded.

Our preferred sample includes workers with at least 2 observations and firms with at least 5 movers. When applying these restrictions, the correlation between unobservables is estimated to be 0.048 and the correlation between the total of observable and unobservable firm and worker characteristics is estimated to be 0.105.

C. *Measuring Openness*

We use several measures of openness at the industry level in order to capture different aspects of openness to trade and other international economic activities. We do not use firm-level measures of openness to avoid the endogeneity problem.

Our preferred measure of openness is tariffs. Reduction in foreign tariffs imposed on Swedish exports can increase the market access for Swedish firms, while reduction in Swedish tariffs imposed on foreign imports may intensify import competition. 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 any substantial impact on the level of tariffs set by the EU. In addition, foreign tariffs are not affected by conditions in the Swedish industry. Data on tariffs (at the six-digit HS) are from the UNCTAD TRAINS database. This classification is then aggregated up to the three-digit level of SNI (Swedish Industrial Classification) using trade shares as weights. 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.

Our second industry-level measure of openness is the production share of multinational firms (both foreign and Swedish owned) in total production (measured in sales). 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. This variable can capture the degree of outsourcing and offshoring, which is another important aspect of openness.

All measures imply that openness has increased between 1995 and 2005. The share of multinational firms in sales has increased from about 47 percent to 55 percent. There has also been a sharp decrease in tariffs during this period.

D. Defining the Trade Orientation of an Industry

We define an industry as export oriented if the industry has net exports in the initial period of the sample, and an industry as import competing if the industry has net imports in the initial period of the sample. According to this definition, export-oriented industries include the Manufacture of pulp, paper and paperboard; Manufacture of motor vehicles; Manufacture of pharmaceuticals, medicinal chemicals and botanical products; Manufacture of other special purpose machinery, etc. This list of export-oriented industries clearly indicates that Sweden has the comparative advantage in high-tech products as well as wood related products (related to its natural endowments). On the other hand, import-competing industries include the Manufacture of wearing apparel and accessories; Manufacture of footwear; Manufacture of rubber products; Manufacture of basic chemicals, etc.

As robustness checks, we define the trade orientation of an industry based on the average of net exports across years. An industry is defined as export oriented if it has 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 export oriented if it has 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 alternative measures. Moreover, we experiment with a continuous measure of trade status by calculating the value of net exports as a share of total trade (imports plus exports).

4. Empirical Results on Openness and Matching

A. Baseline estimates

Table 3 reports the estimation results for equation (1). All regressions include industry and year fixed effects. Standard errors are clustered at the 3-digit SNI industry level. An industry is considered as export oriented if the industry had positive net exports in 1995. Column 1 reports the results when openness is measured by foreign tariffs on Swedish exports. Note that the tariff data are transformed so that more openness means lower tariffs. The estimated coefficient on openness is negative, but statistically insignificant. This suggests that for import-competing industries, reduced foreign tariffs have no significant effect on the degree of matching. The estimated coefficient on the interaction term is 0.022 with a standard error of 0.007, indicating that the effect of reduced foreign tariffs on the degree of matching is significantly different between import-competing and export-oriented industries. In particular, the estimates in column 1 suggest that for export-oriented industries, reduced foreign tariffs significantly improve the degree of matching. This result provides strong support for the DMS model. Reduced foreign tariffs can improve the opportunity for Swedish firms to enter or expand their presence in foreign markets. As the DMS model suggests, good firms in export-oriented industries will benefit more from the increased access to world markets and will hire more highly-skilled workers. On the other hand, weak firms in export-oriented industries will become less able to attract highly-skilled workers. As a result, the degree of positive assortative matching increases in export-oriented industries.

Column 2 of Table 3 displays the results when openness is measured by Swedish tariffs imposed on foreign goods. Again, the tariff data are transformed so that greater openness means reduced Swedish tariffs. Unlike the estimates in column 1, we find no significant effect of openness on the degree of matching for either import-competing or export-oriented industries. 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. On the other hand, lower Swedish tariffs may benefit Swedish producers who use the imported goods as an intermediate input. 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.

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 related to outsourcing or offshoring. Thus, this measure of openness helps to capture another aspect of increasing economic integration. The estimates in column 3 show that increased share of multinational sales weakly reduce the degree of matching for import-competing industries. Consistent with the result in column 1, the estimated coefficient on the interaction term is statistically significant and positive. The results suggest that the effect of increased sales by multinational firms on the degree of matching is significantly positive for export-oriented industries. In column 4 we include an additional five industries that do not have tariff data available. The results are little changed.

Overall, we find strong evidence that greater openness improves the degree of positive assortative matching for export-oriented industries, which supports the theoretical prediction of the DMS model. On the other hand, we find no strong evidence that more openness has any significant effect on the degree of matching for import competing industries. This is also broadly consistent with the extension of the DMS model that allows for monopolistic competition in the product market. As discussed earlier, the impact of openness on the efficiency of matching in import-competing industries is ambiguous in that framework.

B. Skill-based Technical Change

In Acemoglu (1999) and Albrecht and Vroman (2002) search models are developed in which skill-biased technical change increases the degree of positive assortative matching. 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, which include the share of investment in computing and communication equipment, R&D expenditures per employee, annual growth rate in capital stock, and annual growth rate in capital intensity. The results are given in Table 4. Columns 1-5 report the estimates when openness is measured by foreign tariffs. Columns 6-10 report the results when openness is measured by the share of multinational sales. The table shows that 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.

C. Domestic deregulations and product market competition

There were no major reforms during the period we are looking at. However, the shift of 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 5.

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. Both columns 1 and 3 show that more anti-competitive regulations lead to a higher degree of positive assortative matching. This may indicate that high-tech firms benefit more from anti-competitive regulations and hire more highly-skilled workers. On the other hand, our results for the effect of openness remain unchanged.

We also construct a measure of product market competition at the two-digit industry level by following Boone (2008) and Boone et al. (2007). A higher value of the measure indicates more competition. The results reported in columns 2 and 4 indicate that this measure has no significant effect on the degree of matching. Again, our results for the effect of openness are unchanged.

D. Alternative measures of the degree of matching, openness, and the trade status of an industry

We now examine the robustness of our baseline results to alternative measures of the degree of matching, openness, and the trade status of an industry. The results are displayed in Table 6.

In the baseline estimation the degree of matching is measured as the correlation between firm and worker total effects. In rows 1 and 9 we use an alternative measure of positive assortative matching by correlating the firm total effects with the worker total effects averaged across all workers employed in the firm. In rows 2 and 10 we replace the measure by a correlation between the firm total effects with the median worker total effects for all workers employed in the firms. Both alternative measures generate fairly similar results for the effect of openness on the degree of matching. The estimates suggest that more openness (measured as reduced foreign tariffs in panel A and as increased share of multinational sales in panel B) significantly increase the degree of positive assortative matching for export-oriented industries, but weakly reduce the degree of matching for import-competing industries. Thus, these results are consistent with our baseline estimates.

All the measures of the degree of matching reported so far are constructed using the estimates of the wage regression specified in equation (2). The benefit of this approach is that we can correlate both observed and unobserved firm and worker attributes. However, if the sample period is short, the estimated worker unobserved effects may have finite sample bias. In addition, identification of firm unobserved effects relies on wages of movers only, which could generate bias in the estimates of firm unobserved effects. Given these possible limitations, we also construct the measure of the degree of matching based on observed worker and firm attributes. Specifically, we measure worker skills by education, which is classified at seven different levels (see Table A1 in the Appendix for details). We measure firm types using capital intensity. More capital intensive firms tend to use more sophisticated technology and thus we treat them as high-tech firms. Rows 3 and 11 report the results when the degree of matching is measured as a correlation between worker education levels and firm capital intensity. Again, we find strong evidence that increased openness (reduced foreign tariffs or an increased share of multinational sales) significantly improves the degree of positive assortative matching for the export-oriented industries.

In rows 5 and 13 we replace the contemporaneous measures of openness with those at a one-year lag. The key results remain unchanged.

We then estimate the effect of openness on positive assortative matching using alternative definitions of the trade status of an industry. In rows 5 and 12 an industry is defined as export oriented if the industry has a positive average of net exports over the sample period. In rows 6 and 13 an industry is defined as export oriented if the industry has more years with positive net exports than with negative net exports. As mentioned in the data section, 90% of industries have consistent trade status based on these alternative measures. Thus, it is no surprise that the estimates based on these alternative definitions of trade status are very close to the baseline estimates reported in Table 3. In rows 7 and 14 we use a continuous measure of trade orientation by calculating a ratio of net exports to total trade (exports plus imports). Again, the baseline results carry through.

Overall, Table 6 shows that our key result remains unchanged when alternative measures of the degree of matching, openness, and trade status are used: increased openness increases the degree of matching for export-oriented industries.

E. First-difference specification

The regressions reported in Table 3 fully exploit information for each year over the sample period. In order to examine whether the estimates shown in Table 3 can also capture the long-term relationship between openness and matching, we take a simple 10-year difference of the data and look at the relationship between the change in openness and the change in the degree of matching across 74 SNI industries for 1995-2005. The results are shown in Table 7. As shown in column 1, a negative coefficient on the change in foreign tariffs suggests that a reduction in foreign tariffs reduces the degree of matching for import-competing industries. The estimated coefficient on the interaction between trade status of an industry and openness is significantly positive and the magnitude is substantially larger than that in the first row, which suggests that reduced foreign tariffs significantly improve matching for export-oriented industries. Moreover, column 2 shows that the degree of matching is not affected by reduced Swedish tariffs. Finally, column 3 confirms our previous results that there is a positive effect on the degree of matching from the presence of multinational firms in export oriented industries.

5. Conclusion

As far as we know, this is the first empirical paper to investigate the impact of globalization on the efficiency of matching between heterogeneous firms and heterogeneous workers within industries. Using matched worker-firm data from Sweden, we find strong evidence that increased openness improves the matching process in export-oriented industries while having no significant effect on matching in import-competing industries. These results are quite robust, holding for alternative measures of our key variables and persisting when we control for technical change at the industry level, domestic anti-competitive regulations and product market competition. 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.

Our empirical methodology is based on Abowd, Kramarz and Margolis (1999). Recent extensions and modifications of that approach suggest at least two additional robustness checks that we intend to explore in the next version of this paper. The AKM wage regression includes worker and firm fixed effects aimed at ranking workers and firms in terms of their productivities. Woodcock (2008a, b) adds a match effect to the wage equation and argues that this effect is a key determinant of earnings dispersion. He argues that "specifications that omit match effects substantially over-estimate the returns to experience, attribute too much variation to personal heterogeneity, and underestimate the extent to which good workers sort into employment at good firms." Computational limitations make it impossible to add match effects to our wage regression when using our preferred data set. In the future, we intend to check for the robustness of our results to the inclusion of match effects in randomly selected sub-samples of our data.

Our second extension will be in response to the recent criticism of the AKM approach by Lopes de Melo (2009). He considers a model with on-the-job search, very much in the spirit of Shimer and Smith (2000), 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 is that stronger firms will be in a better bargaining position with weak workers and maybe 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. Lopes de Melo's primary goal is to explain why previous empirical work using the AKM approach has failed to find evidence of positive assortative matching in the labor market. He argues that this may be due to the inability of the AKM approach to generate firm effects that correctly rank the firms in terms of their productivities. He suggests an alternative test for positive assortative matching by correlating worker effects with the average effects of co-workers. While this may be an appropriate alternative method to test for positive sorting, it is unclear whether this approach can be used to examine the *change* in the degree of matching between workers and firms. This is a theoretical issue that we are currently examining and, if appropriate, future versions of this paper we include Lopes de Melo measures of positive assortative matching.

References

Abowd, John M., Francis Kramarz and David N. Margolis (1999). High wage workers and high wage firms. *Econometrica* 67(2): 251-333.

Abowd, J., R. Creecy, and F. Kramarz (2002). Computing person and firm effects using linked longitudinal employer-employee data. Technical Paper 2002-06, U.S. Census Bureau.

Acemoglu, Daron (1999). Changes in unemployment and wage inequality: An alternative theory and some evidence. *American Economic Review* 89: 1259-78.

Albrecht, James and Susan Vroman (2002). A matching model with endogenous skill requirements. *International Economics Review* 43(1): 282-305.

Andrews, Martyn, Thorsten Schank and Richard Upward (2006). Practical fixed-effects estimation methods for the three-way error-components model, *Stata Journal* 6 (4): 461-81.

Andrews, Martyn; Len Gill; Thorsten Schank, and Richard Upward (2008). High wage workers and low wage firms: Negative assortative matching or limited mobility bias? *Journal of the Royal Statistical Society Series A* 171(3): 693-97.

Autor, David; Lawrence Katz, and Melissa Kearney (2006). The polarization of the U.S. labor market. *American Economic Review Papers and Proceedings,* 96(2): 189-94.

Antràs, Pol; Luis Garicano, and Esteban Rossi-Hansberg (2006). Offshoring in a knowledge economy. *Quarterly Journal of Economics,* 121(1): 31-77.

Barro, Robert and Jong-Wha Lee (1993). International comparisons of educational attainment. *Journal of Monetary Economics,* 32: 363-94.

Barro, Robert and Jong-Wha Lee (1996). International measures of schooling years and schooling quality. *American Economic Review,* 86: 218-23.

Barro, Robert and Jong-Wha Lee (2001). International data on educational attainment: Updates and implications, *Oxford Economic Papers,* 53: 541-63.

Barth, E. and H. Dale-Olsen (2003). Assortative matching in the labour market? Stylised facts about workers and plants. Mimeo, Institute for Social Research, Oslo.

Becker, Gary (1973). A theory of marriage: Part I. *Journal of Political Economy* 81(4): 813-46.

Bernard, Andrew; Jonathan Eaton; J. Bradford Jensen; and Samuel Kortum (2003). Plants and productivity in international trade. *American Economic Review* 94(3): 1265-90.

Bernard, Andrew; J. Branford Jensen; Stephen Redding and Peter Schott (2007). Firms in international trade. *Journal of Economic Perspectives* 21(3): 105-30.

Boone, Jan (2008). A new way to measure competition. *Economic Journal* 118(531): 1245-61.

Boone, Jan; Jan Van Ours; and Henry van der Wiel (2007). How (not) to measure competition. *TILEC Discussion Paper* No. 2007-014.

Cornelissen, T. (2006). Using Stata for a memory saving fixed effects estimation on the three-way error component model, FDZ Methodenreport Nr. 3/2006. Published in Stata Journal 8, 2008.

Cornelissen, T. and O. Hubler (2007). Unobserved individual and firm heterogeneity in wage and tenure functions: Evidence from German linked employer-employee data, IZA Discussion Paper No. 2741.

Costinot, Arnaud (2009). An elementary theory of comparative advantage. *Econometrica,* 77(4): 1165-92.

Costinot, Arnaud and Jonathan Vogel (2010). Matching and inequality in the world economy. *Journal of Political Economy*, 118(4): 747-86.

Davidson, Carl; Steven Matusz and Andrei Shevchenko (2008). Globalization and firm level adjustment with imperfect labor markets. *Journal of International Economics,* 75(2): 295-309.

Davidson, Carl and Steven Matusz (2010). Globalization and imperfect matching with monopolistic competition. Michigan State University.

Davis, Stephen; John Haltiwanger and Scott Schuh (1996). *Job Creation and Job Destruction*. Cambridge, MA: MIT Press.

Doms, Mark; Timothy Dunne; and Kenneth Troske (1997). Wages, workers, and technology. *Quarterly Journal of Economics* 112(1): 252-90.

Goos, Maarten and Alan Manning (2007). Lousy and lovely jobs: The rising polarization of work in Britain. *Review of Economics and Statistics* 89 (1): 118-33.

Goos, Maarten; Alan Manning; and Anna Salomons (2009). The polarization of the European labor market. *American Economic Review*, 99(2): 58-63.

Goux, D. and E. Maurin (1999). Persistence of inter-industry wage differentials: a reexamination using matched worker-Firm panel data. *Journal of Labor Economics* 17, 492-533.

Grossman, Gene (2004). The distribution of talent and the pattern and consequences of international trade. *Journal of Political Economy,* 112: 209-39.

Grossman, Gene and Giovanni Maggi (2000). Diversity and trade. *American Economic Review*, 90: 1255-75.

Gruetter, M. and R. Lalive (2004). The importance of Firms in wage determination. Discussion Paper No. 1367, IZA.

Kremer, Michael and Eric Maskin (2006). Globalization and inequality, Harvard University Working Paper.

Legros, Patrick and Andrew Newman (2002). Monotone matching in perfect and imperfect worlds. *Review of Economic Studies,* 69: 925-42.

Legros, Patrick and Andrew Newman (2007). Beauty is a beast, frog is a prince: Assortative matching with non-transferabilities. *Econometrica,* 75(4): 1073-1102.

Lopes de Melo, Rapael (2009). Sorting in the labor market: Theory and measurement, University of Chicago Working Paper.

Melitz, Marc (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica,* 71: 1695-1725.

Ohnsorge, Franziska and Daniel Trefler (2007). Sorting it out: International trade with heterogeneous workers. *Journal of Political Economy,* 115(5): 868-92.

Roy, Andrew (1951). Some thoughts on the distribution of earnings. *Oxford Economic Papers* 3: 135-46.

Sattinger, Michael (1993). Assignment models of the distribution of earnings. *Journal of Economic Literature,* 31(2): 831-80.

Shimer, Robert and Lones Smith (2000). Assortative matching and search. *Econometrica,* 68(2): 343-69.

Tinbergen, Jan (1951). Some remarks on the distribution of labour incomes. In *International Economic Papers, No. 1,* A. Peacock et al (eds), London: Macmillan; 195-207.

Woodcock, Simon (2008a). Wage differentials in the presence of unobserved worker, firm, and match heterogeneity. *Labour Economics* 15(4): 771-93.

Woodcock, Simon (2008b). Match effects. Available at SSRN: http://ssrn.com/abstract=931529.

Yeaple, Stephen (2005). A simple model of firm heterogeneity, international trade, and wages. *Journal of International Economics,* 65: 1-20.

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.

	Total sample		Total sample with trade		Net importer		Net exporter	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Dependent variable								
Correlation total effects	0.1047	0.0000	0.0713	0.0000	0.0995	0.0000	0.0242	0.0000
Individual level variables								
Wage	19817.09	1.3703	20054.32	1.3557	19219.87	1.3618	20629.97	1.3470
Experience	22.9418	12.3142	23.5457	12.1163	24.2768	12.2644	23.0591	11.9920
Experience^2	677.9647	599.3728	701.2014	604.7058	739.7786	619.6069	675.528	593.1934
Blue collar	0.4885	0.4999	0.6036	0.4892	0.5954	0.4908	0.6090	0.4880
Firm level variables								
Capital intensity	0.1533	5.4254	0.2626	3.5909	0.1789	3.4622	0.3392	3.4473
Share of females	0.3537	0.2231	0.2722	0.1397	0.3151	0.1390	0.2437	0.1327
Share of high educated	0.2500	0.1949	0.2281	0.1589	0.2077	0.1522	0.2418	0.1618
Size	1370.73	5.6497	1307.27	4.9540	852.35	4.8086	1737.84	4.7394
Labor productivity	0.4893	1.9211	0.5149	2.1667	0.4097	2.1596	0.5995	0.9412
Industry level variables								
MNE share	0.5149	0.3317	0.6662	0.2873	0.6404	0.2892	0.7005	0.2814
Foreign tariffs	1.7454	9.6652	1.7473	9.6702	2.5969	12.7201	0.6201	0.9286
Swedish tariffs	0.8291	1.1722	0.8291	1.1722	1.1675	1.4116	0.3803	0.4496
ICT investments	0.2451	0.1985	0.2093	0.2144	0.2197	0.2420	0.1955	0.1705
R&D intensity	60617.8	95092.34	63593.79	97821.15	60313.97	102557	68380.32	90393.63
Growth in capital	0.1326	0.5000	0.0827	0.4123	0.0704	0.3619	0.0991	0.4707
Growth in capital intensity	0.4756	1.8925	0.3254	1.1682	0.3356	1.1957	0.3118	1.1322

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	

Tables and Figures

Figure 1. Assortative matching and openness

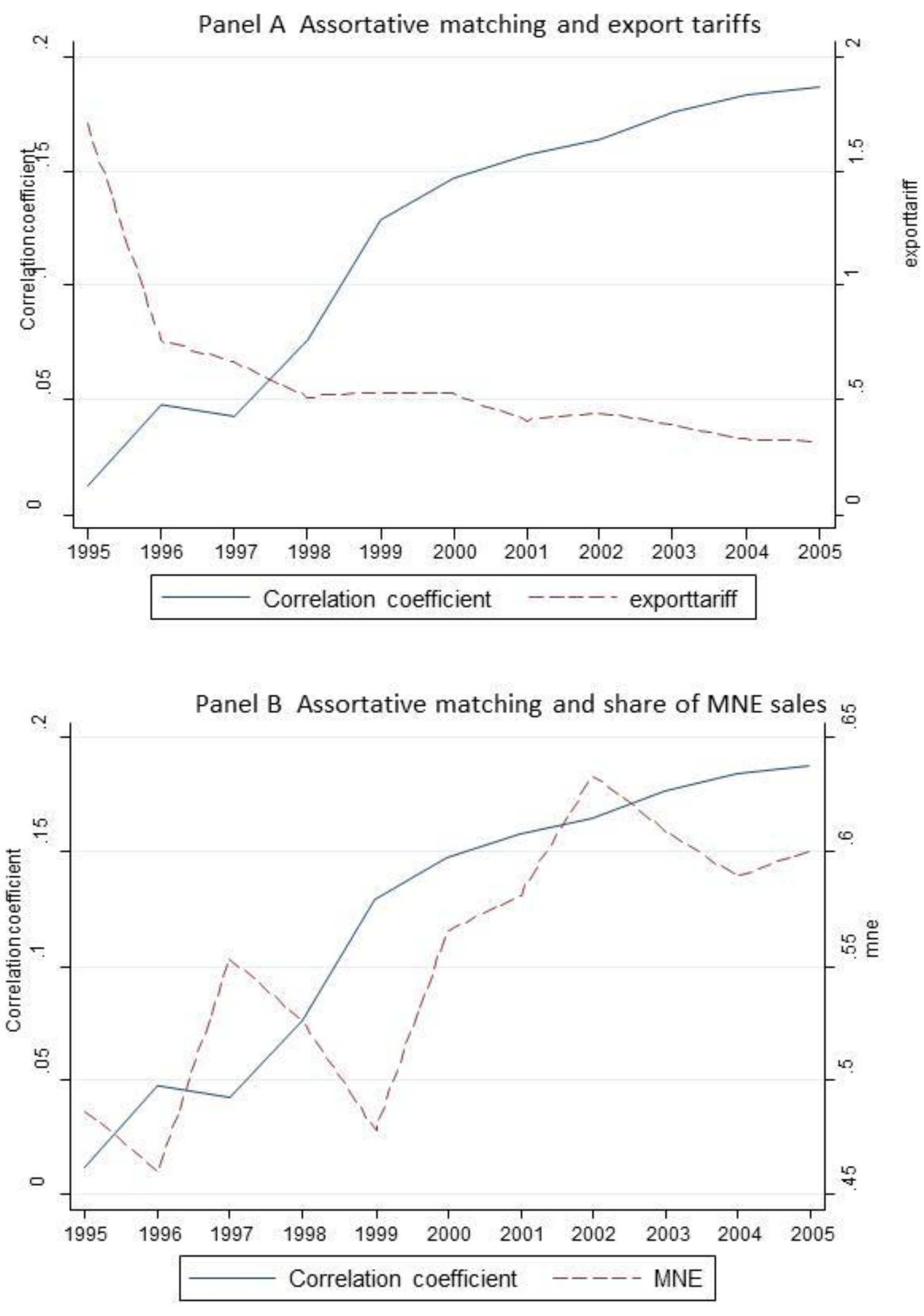

Figure 2. The Basic DMS Framework. How do changes in openness affect M?

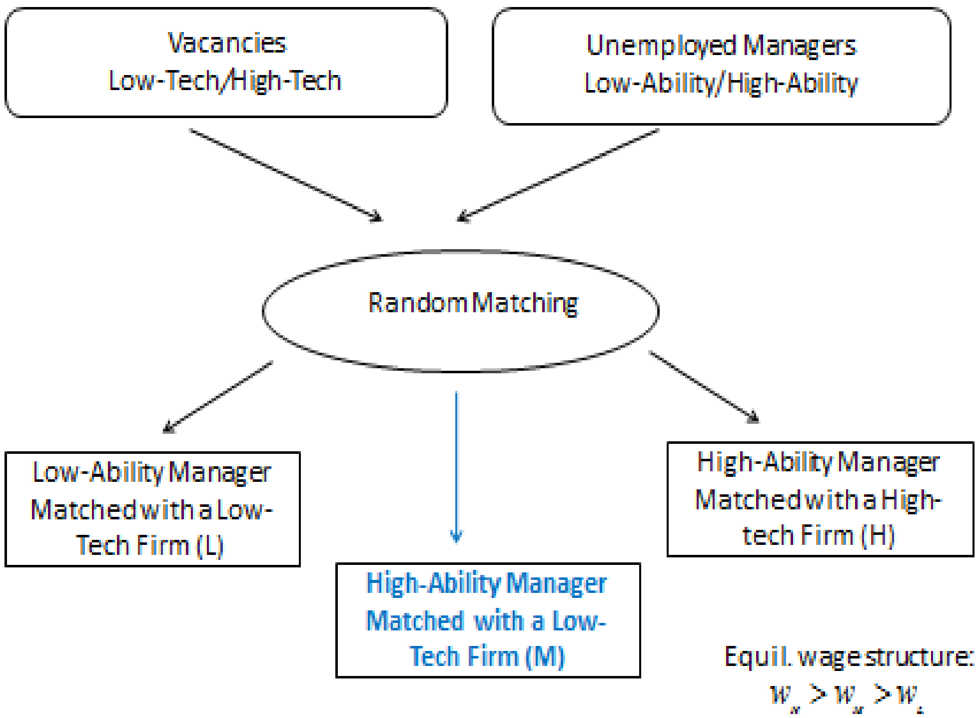

Table 1. Individual Worker Wage Regressions 1995-2005

	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-square	0.4075	

Table 2 Correlations Between Firm and Worker Attributes 1995-1995

	Correlation between firm and worker unobservable effects	Correlation between firm and workers total effects
Whole sample:	0.0655	0.1076
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 9,450,919 observations, and the *preferred sample* has 8,977,269 observations.

Table 3: Openness and assortative matching: baseline results

	Foreign tariffs	Swedish tariffs	MNE share	MNE share (extended sample)
	(1)	(2)	(3)	(4)
Openness	-0.001	0.018	-0.0695*	-0.0542
	(0.002)	(0.015)	(0.0401)	(0.0409)
Export_oriented*Openness	0.022***	0.008	0.2870**	0.2868***
	(0.007)	(0.022)	(0.1208)	(0.1184)
Observations	860	860	860	915
R-squared (within)	0.057	0.052	0.079	0.092
Number of industries	88	88	88	93

Notes: In all the regressions the dependent variable is the degree of matching measured as the correlation between firm and person total effects by industry and year. Industry and year fixed effects are included. Standard errors reported in parentheses are clustered by industries. An industry is defined as export oriented if this industry has positive net export for 1995. *** p<0.01, ** p<0.05, * p<0.1

Table 4. Controlling for technology change at the industry level

	Foreign tariffs					MNE share				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Openness	-0.001	-0.001	-0.001	-0.011	-0.001	-0.0535	-0.0718*	-0.0543	-0.0549	-0.0726*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.0404)	(0.0427)	(0.041)	(0.0407)	-0.0428
Export_oriented*Openness	0.023***	0.022***	0.023***	0.023***	0.022***	0.2855**	0.3734***	0.2872**	0.2883***	0.3735***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.1187)	(0.1066)	(0.119)	(0.1186)	-0.1071
ICT investments	-0.0139				-0.0233	-0.0346				-0.0206
	(0.0336)				(0.0337)	(0.0349)				(0.0325)
R&D intensity		0.0003			0.0003		0.0003			0.0003
		(0.0002)			(0.0002)		(0.0002)			(0.0002)
Growth in capital			0.0074		-0.0004			-0.0008		-0.0025
			(0.0062)		(0.0032)			(0.0038)		(0.0031)
Growth in capital intensity				0.0068	0.0059				-0.002	0.0061
				(0.0043)	(0.0045)				(0.0049)	(0.0046)
Observations	860	816	855	855	816	915	816	915	912	816
R-squared (within)	0.06	0.07	0.06	0.05	0.07	0.09	0.11	0.09	0.09	0.1082
Number of industries	88	84	88	88	84	93	84	93	93	84

Note: ICT investments is the share of ICT in total investments. R&D is expenditures per employee. Growth in capital and capital intensity are annual growth rates.

Table 5. Controlling for domestic deregulations and product market competition

	Foreign tariffs		MNE share	
Openness	-0.001	-0.001	-0,059	-0.0863**
	(0.001)	(0.002)	(0.0411)	(0.0399)
Export_oriented*Openness	0.018***	0.020***	0.2677**	0.3879***
	(0.007)	(0.008)	(0.1082)	(0.1064)
Regulatory Impact Indicator	11.1211**		10.9665**	
	(5.336)		(5.317)	
Product Market Competition		0,0035		0,0037
		(0.0027)		(0.0025)
Observations	860	769	860	769
R-squared	0,0727	0,0739	0,0941	0,1158
Number of industries	88	77	88	77

Table 6 Robustness

	Openness Coeff.	Openness Std Err	Export_oriented*Openness Coeff.	Export_oriented*Openness Std Err	Observations	R-squared (within)	# industries
			A. Openness is measured by foreign tariffs				
Alternative measure of matching							
(1) Firm effect and average worker effect	-0.011*	0.006	0.084***	0.027	860	0.039	88
(2) Firm effect and median worker effect	-0.010*	0.006	0.089***	0.019	860	0.033	88
(3) Schooling and capital intensity	-0.001	0.002	0.018**	0.008	860	0.047	88
Alternative measure of openness							
(4) Openness at a 1-year lag	-0.005***	(0.0016)	0.037***	(0.0055)	766	0.083	87
Alternative measure of trade status							
(5) Net_exporter2	-0.001	(0.0014)	0.024***	(0.0067)	860	0.059	88
(6) Net_exporter3	-0.001	(0.0014)	0.024***	(0.0066)	860	0.059	88
(7) Net_exporter4	0.014***	(0.003)	0.035***	(0.0073)	860	0.065	88
			B. Openess is measured by MNE shares				
Alternative measure of matching							
(8) Firm effect and average worker effect	-0.1852	0.224	0.8709*	0.444	860	0.049	88
(9) Firm effect and median worker effect	-0.5481**	0.265	1.1003**	0.464	860	0.052	88
(10) Schooling and capital intensity	0.0329	0.026	0.2018**	0.095	860	0.085	88
Alternative measure of openness							
(11) Openness at a 1-year lag	-0.0157	(0.0315)	0.256***	(0.0905)	766	0.091	87
Alternative measure of trade status							
(12) Net_exporter2	-0.0727*	(0.0368)	0.3614***	(0.1008)	860	0.092	88
(13) Net_exporter3	-0.0675	(0.042)	0.2605**	(0.1173)	860	0.075	88
(14) Net_exporter4	0.0699	(0.0579)	0.3570**	(0.1587)	860	0.073	88

Notes: Industry and year fixed effects are included in all regressions. In rows 5 and 12 an industry is defined as export oriented if this industry has a positive average of net exports over the period 1995-2005. In rows 6 and 13 an industry is defined as export oriented if it has more years with positive net exports than with negative net exports. In rows 7 and 14 a continues variable on export orientation is constructed as: net exports/(exports+imports). Standard errors reported in parentheses are clustered by industries. *** p<0.01, ** p<0.05, * p<0.1

Table 7 Openness and assortative matching: First-difference regressions for 1995-2005

	(1)	(2)	(3)
	Foreign tariffs	Swedish tariffs	MNE share
ΔOpenness	0.018	0.0018	-0.0923
	(0.022)	(0.0273)	(0.1401)
Export oriented*ΔOpenness	-0.0635***	0.0489	0.5017**
	(0.0238)	(0.0601)	(0.199)
Export_oriented	-0.1334**	-0.0017	-0.0801
	(0.0569)	(0.087)	(0.0516)
Observations	74	74	74
R-squared	0.111	0.022	0.083

Notes: The dependent variable in all regressions is a 10 year difference of the degree of matching, measured as the correlation between firm and person effects. Standard errors reported in parentheses are clustered by industries. An industry is defined as export oriented if this industry has positive net export for 1995.