



Globalization and Labour Market Outcomes

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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 comparative-advantage 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 comparative-disadvantage 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 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 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 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 is 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 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

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

market sorting and (b) in comparative-disadvantage industries greater openness may increase the mismatch between workers and firms.³ 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 increases market access for Swedish firms, while a 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 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 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.

³ 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.

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 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 comparative-advantage and comparative-disadvantage 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 comparative-advantage 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 matching in the labor market. On the other hand, we find no evidence that openness affects the degree of matching in comparative-disadvantage 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. 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.⁴ 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 sever relationships in search of

⁴ 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-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.⁵ 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 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.

⁵ 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 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 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 and the rental rate is normalized to one. 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 then 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 in equilibrium. The value

of γ summarizes what we need to know about the mix of open jobs 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 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 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 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.

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 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.

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 similar to the Ex-Post Segmentation 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 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 separating equilibrium to a pooling equilibrium.⁶ 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 many industries middling jobs have been disappearing and have been replaced by the type of jobs that would be offered in a separating equilibrium.⁷

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

⁶ See Albrecht and Vroman (2002) for a similar argument.

⁷ 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.

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 comparative-advantage industries, but may reduce the degree of positive assortative matching in comparative-disadvantage industries. To examine these theoretical predictions, we use the following specification:

$$Matching_{gt} = \alpha_0 + \alpha_1 Openness_{gt} + \alpha_2 Comparative - advantage industry_g \cdot Openness_{gt} + D_t + D_g + \mu_{gt} \quad (1)$$

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; $Comparative - advantage industry_g$ is a dummy variable equal to one if g is a comparative-advantage industry, zero otherwise;⁸ 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 affect the degree of matching. The industry fixed effects may capture the cross-industry difference in the degree of matching as a result of differences in production technology across industries. Because specification (1) controls for both year and industry fixed effects, identification of the openness effect on matching relies on within-industry over-time variation in the degree of matching and openness. In addition, the DMS model predicts that the effect of openness on the degree of matching should vary systematically across industries by trade status. Thus, we use the difference-in-difference approach as specified in equation (1) where α_2 indicates the difference in the effect of openness between

⁸ 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.

comparative-advantage and comparative-disadvantage industries and should be significantly positive as predicted by the DMS model. This sharp 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 comparative-advantage and comparative-disadvantage industries.

Our main coefficients of interest are α_1 and α_2 . The effect of openness on the degree of matching for comparative-disadvantage industries is captured by α_1 , and the effect of openness for comparative-advantage industries is captured by $\alpha_1 + \alpha_2$. If the effect of openness is negative for comparative-disadvantage industries, but positive for comparative-advantage industries, we expect that α_1 is significantly negative, and that $\alpha_1 + \alpha_2$ 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 1995-2005.⁹ 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.¹⁰

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.

⁹ 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.

¹⁰ The plant-level data are aggregated to the firm level. In the following, we only use 'firms.'

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. 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. 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.

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

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

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, and ν_{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.¹¹ Time-varying worker characteristics include experience squared, higher-degree polynomials of experience, and a dummy variable for blue-collar

¹¹ The wages for female workers who take a maternity leave are reported as the same as prior to their leave.

occupations.¹² 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.¹³ Note that the omission of observed 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 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 et al., 2006). We include firm dummies and sweep out the worker effects by the within transformation. Firm effects are identified from workers who move between firms over the period. Non-movers add nothing to the estimation of the firm effects so the firm effect will not be identified for firms with no movers. Worker effects are estimated from repeated observations per worker, implying that the data must include a sufficient number of both multiple observations of workers and movers of individuals across firms. This approach, labeled as FEiLSDVj¹⁴ 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 in our sample is four (see Table A3

¹² 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).

¹³ 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.

¹⁴ 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.

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). 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.

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 $Z_{j(h,t)}\lambda + \phi_{j(h,t)}$) 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 ($Z_{j(h,t)}\lambda + \phi_{j(h,t)}$). 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 et al. (2008) who analyze how sensitive the correlation is to the share of movers in the data. They report a positive correlation when they study movers in high turnover plants. Table A5 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 the market access for Swedish firms. A reduction in Swedish tariffs imposed on foreign imports may intensify import competition for final good producers, but may 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.¹⁵ 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.¹⁶ Over the sample period, the share of sales by multinational firms increased steadily.

D. Defining the Trade Orientation of an Industry

We define an industry as having a comparative advantage if the industry had positive net exports in 1995, and an industry as having a comparative disadvantage if the industry had positive net imports in 1995. This definition is consistent with theoretical trade models with perfect competition or monopolistic competition. According to this definition, comparative-advantage 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 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, comparative-disadvantage industries

¹⁵ SNI roughly corresponds to Standard Industrial Classification (SIC).

¹⁶ Unlike tariffs, the share of sales by multinational firms may be affected by the degree of matching. Thus, in the empirical analysis we will use the data on Finnish FDI as an instrument for the multinational sales.

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 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 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 2 reports the results for equation (1). In this table, openness is measured by foreign tariffs on Swedish exports, and an industry is considered as having a comparative advantage if this industry had positive net exports in 1995. Note that the tariff data are transformed so that more openness means lower tariffs. 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 openness is negative, but statistically insignificant. This suggests that for comparative-disadvantage 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 comparative-advantage and comparative-disadvantage industries. In addition, as shown at the bottom of column 1, the F -test of the hypothesis of $\alpha_1 + \alpha_2 > 0$ suggests that the hypothesis cannot be rejected at a significance level less than

0.001. That is, for comparative-advantage industries, reduced foreign tariffs significantly improve the degree of matching, which provides strong support for the DMS model. A reduction in 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 comparative-advantage 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 comparative-advantage industries will become less able to attract highly-skilled workers. As a result, the degree of positive assortative matching increases in comparative-advantage industries.

There is one possible explanation of the weaker result for comparative-disadvantage industries. Openness here is measured as reduced foreign tariffs. Because comparative-advantage industries have a higher percentage of firms that export than comparative-disadvantage industries and reduced foreign tariffs will directly and mainly benefit the firms that export, we expect reduced foreign tariffs to have a stronger effect on the degree of matching in comparative-advantage industries than in comparative-disadvantage industries.

Column 2 reports the results when the degree of matching is alternatively measured by correlating the firm total effects with the worker total effects averaged across all workers employed in the firm. Column 3 shows the estimates when the degree of matching is measured by a correlation between the firm total effects with the 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 significantly increase the degree of positive assortative matching for comparative-advantage industries, but weakly reduce the degree of matching for comparative-disadvantage industries. Thus, these results are consistent with our baseline estimates as shown in column 1.

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. Column 4 reports 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) significantly improves the degree of positive assortative matching for the 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 comparative-disadvantage industries.

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 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 add annual growth rate in capital stock, and annual growth rate in capital intensity as additional controls. As shown in Table 3, 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, 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 4.

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.¹⁷ Column 1 of Table 4 shows that more anti-competitive regulations lead to a higher degree of positive assortative matching. This may indicate that high-tech firms benefit more from anti-competitive regulations and hire more highly-skilled workers. On the other hand, our results for the effect of openness remain unchanged.

We also construct a measure of product market competition at the two-digit industry level by following Boone (2008) and Boone et al. (2007). This measure is based on the within-industry elasticity of profits with respect to marginal costs.¹⁸ The higher the absolute value of this elasticity, the fiercer is competition. The results reported in columns 2 of Table 4 indicate that this measure has no significant effect on the degree of matching. Again, our results for the effect of openness are unchanged.

¹⁷ 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.

¹⁸ 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.

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

We now examine the robustness of our baseline results to alternative measures of the degree of openness and the trade status of an industry. The results are displayed in Tables 5-6.

Column 1 reports the results carried from column 1 of Table 2 when openness is measured by Swedish tariffs imposed on foreign goods. In column 2 we include Swedish tariffs on foreign goods as an alternative measure of openness. Unlike the estimates in column 1, we find no significant effect of openness on the degree of matching for either type of 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. 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 benefit Swedish producers who use the imported goods as an intermediate input. If good firms are more likely to import foreign inputs, the surplus gap would grow between high-tech and low-tech firms. 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. In column 3 we include both foreign tariffs and Swedish tariffs. Our baseline estimates of foreign tariffs are not changed. On the other hand, Swedish tariffs remain statistically insignificant. Therefore, our preferred measure of openness is foreign tariffs imposed on Swedish goods.

In column 4 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 important aspect of increasing economic integration. The estimates in column 4 show that increased share of multinational sales weakly

reduce the degree of matching for comparative-disadvantage 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 comparative-advantage industries.

In columns 5-8 of Table 5 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. The results are reported in Table 6. For comparison, column 1 reports the benchmark results carried from column 1 of Table 2. In column 2, an industry is defined as having a comparative advantage if the industry has a positive average of net exports over the sample period. In column 3 an industry is defined as having a comparative advantage 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. In column 4 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, Tables 5-6 show that our key result remains unchanged when alternative measures of openness and trade status are used: increased openness increases the degree of matching for comparative-advantage industries.

E. Accounting for match effects

The Abowd-Kramarz-Margolis type wage regression can be generalized by including an interaction between workers and firms which is the match effect. The match effect measures returns to time-invariant, unobserved characteristics of worker-firm matches, common to all periods of an employment spell. 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. This 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. However, an ordinary random effects model would impose restrictions on the relationship between observables and unobservables. Instead, Woodcock develops the hybrid mixed effects model which combines fixed effects and random effects estimators.

The degree of matching between workers and firms is still defined as the correlation coefficient between worker and firm total effects. That is, the match effects are excluded from the measurement of the degree of matching. Columns 2-3 of Table 7 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 key result for the comparative-advantage industries is not changed when the match effects are accounted for. On the other hand, unlike columns 1-2, column 3 displays a weakly positive effect of openness on the degree of matching for comparative-disadvantage industries.

F. First-difference specification

The regressions reported in Tables 2-6 fully exploit information for each year over the sample period. In order to examine whether the estimates can also capture a 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 reported in Table 8. As shown in column 1, more openness has no significant impacts on the degree of matching for comparative-disadvantage industries. The interaction between trade status of an industry and the change in openness is significantly positive, indicating that the effect of openness on the degree of matching is significantly larger for comparative-advantage industries than for comparative-disadvantage industries. Furthermore, as suggested by the F -test shown at the bottom of column 1, more openness significantly improves the assortative matching for comparative-advantage industries. In fact, the estimated effect is substantially larger than that reported in column 1 of Table 2 when we look at year-to-year changes. Columns 2-4 report the results when alternative measures of the degree of matching are used. They confirm our previous results that openness has a strong and positive effect on the degree of assortative matching for comparative-advantage 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). 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.” We showed that our results are robust to the inclusion of match effects.

Lopes de Melo (2009) recently criticized the AKM approach. 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.

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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	

Table A5 Correlations Between Firm and Worker Attributes 1995-1995

	Correlation between firm and worker unobservable effects	Correlation between firm and workers total effects
<i>Whole sample:</i>	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
<i>Preferred sample:</i>		
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 sample* has 8,977,269 observations.

Figure 1 Assortative matching and openness

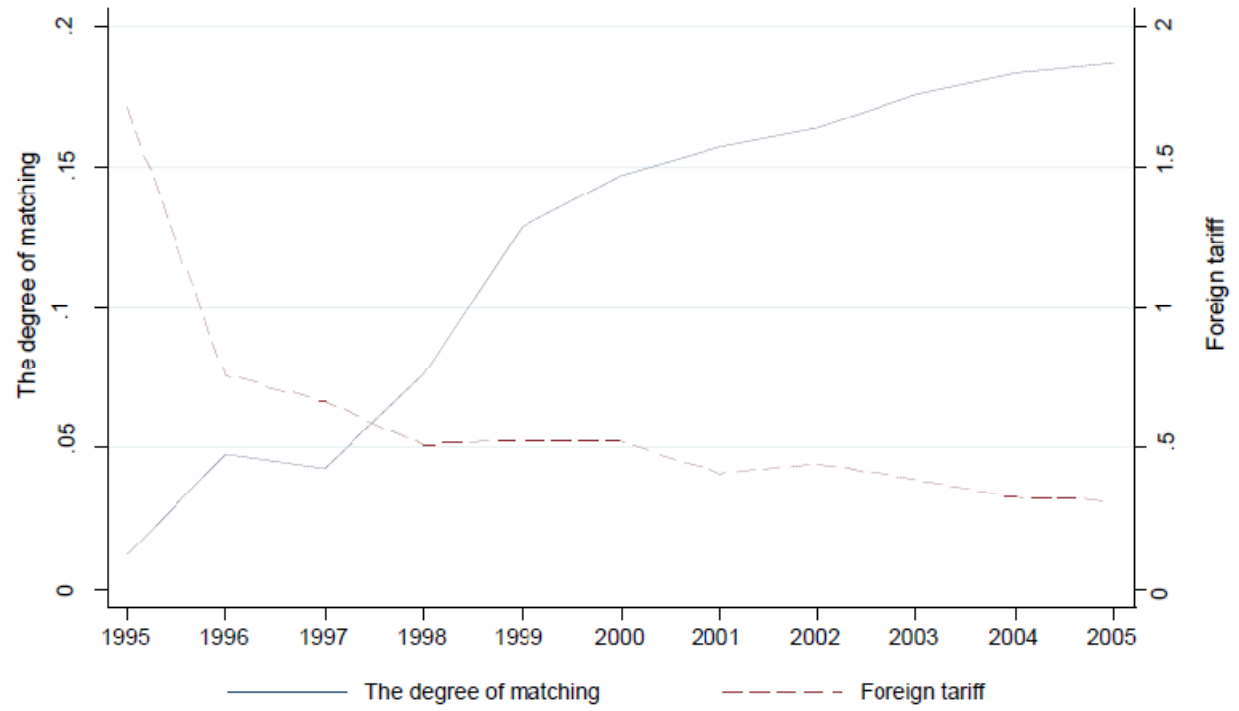


Figure 2. The Basic DMS Framework. How do changes in openness affect M?

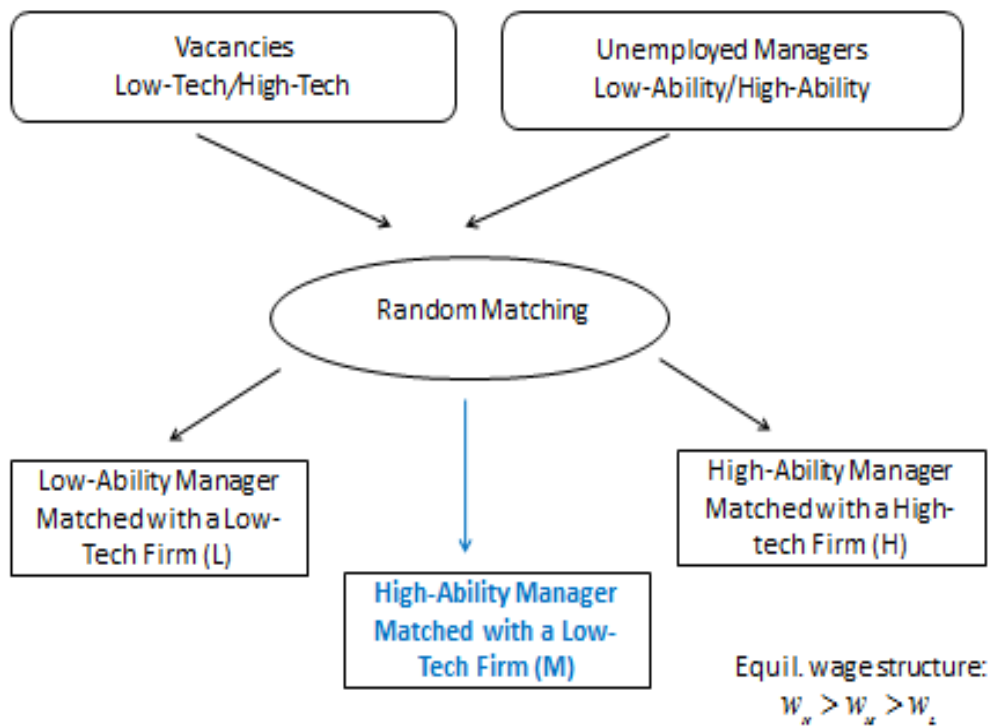


Table 1 Individual Worker Wage Regressions 1995-2005

	OLS	LSDVreg
	(1)	(2)
Experience	0.0243*** (0.0001)	
Experience ² /100	-0.0798*** (0.0009)	-0.001*** (0.0000)
Experience ³ /1000	0.0108*** (0.0003)	0.0012*** (0.0002)
Experience ⁴ /10000	0.0007*** (0.0000)	-0.0006*** (0.0000)
Blue collar	-0.1909*** (0.0002)	-0.0273*** (0.0003)
Female	-0.1394*** (0.0002)	
Capital intensity	0.0494*** (0.0002)	-0.0028*** (0.0001)
Size	0.0003*** (0.0000)	0.0049*** (0.0001)
Labor productivity	0.0494*** (0.0002)	0.0067*** (0.0001)
Share of high skill	0.3376*** (0.0006)	0.0739*** (0.0012)
Manufacturing	0.0214*** (0.0003)	0.0506*** (0.0011)
Share of women	-0.1266*** (0.0005)	0.1297*** (0.0016)
Manufacturing*share of women	0.0327*** (0.0009)	-0.1705*** (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	Capital intensity and worker schooling
	(1)	(2)	(3)	(4)
Openness (α_1)	-0.001 (0.002)	-0.011* (0.006)	-0.010* (0.006)	0.001 (0.002)
Comparative-advantage industry \times Openness (α_2)	0.022*** (0.007)	0.084*** (0.027)	0.089*** (0.019)	0.018** (0.008)
F -test: $\alpha_1 + \alpha_2 > 0$ (p -value)	<0.001	0.002	<0.001	0.006
R^2	0.057	0.039	0.033	0.047

Notes : In all of the regressions 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 capital intensity and worker schooling in column 4. Openness is measured by foreign tariffs on Swedish exports. An industry is defined as having a comparative advantage if this industry has positive net export 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 Controlling for technical change at the industry level

	(1)	(2)	(3)	(4)	(5)
Openness (α_1)	-0.001 (0.002)	-0.001 (0.002)	-0.001 (0.002)	-0.011 (0.002)	-0.001 (0.001)
Comparative-advantage industry \times Openness (α_2)	0.023*** (0.007)	0.022*** (0.007)	0.022*** (0.007)	0.023*** (0.007)	0.022*** (0.007)
ICT investments	-0.014 (0.034)				-0.023 (0.034)
R&D intensity		0.0003 (0.0002)			0.0003 (0.0002)
Growth in capital			0.002 (0.004)		-0.0004 (0.003)
Growth in capital intensity				0.007 (0.004)	0.006 (0.005)
<i>F</i> -test: $\alpha_1 + \alpha_2 > 0$ (<i>p</i> -value)	<0.001	<0.001	<0.001	<0.001	<0.001
R^2	0.06	0.07	0.06	0.05	0.07
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. In all regressions the dependent variable is the degree of matching, which is measured as the correlation coefficient between firm total effects and worker total effects. Openness is measured by foreign tariffs on Swedish exports. An industry is defined as having a comparative advantage if this industry has positive net export for 1995. ICT investments 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 4 Controlling for domestic deregulations and product market competition

	(1)	(2)	(3)
Openness (α_1)	-0.001 (0.001)	-0.001 (0.002)	-0.001 (0.002)
Comparative-advantage industry \times Openness (α_2)	0.018*** (0.007)	0.020*** (0.008)	0.017** (0.007)
Regulatory Impact Indicator	11.121** (5.336)		11.323* (6.586)
Product Market Competition		0.004 (0.003)	0.003 (0.003)
<i>F</i> -test: $\alpha_1 + \alpha_2 > 0$ (<i>p</i> -value)	0.004	0.003	0.011
R ²	0.073	0.074	0.087
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. In all regressions the dependent variable is the degree of matching, which is measured as the correlation coefficient between firm total effects and worker total effects. Openness is measured by foreign tariffs on Swedish exports. An industry is defined as having a comparative advantage if this industry has positive net export for 1995. 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 5 Robustness to alternative measures of openness

	Contemporaneous openness				Openness at a 1-year lag			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Foreign tariffs (α_1^F)	-0.001 (0.002)		-0.001 (0.001)		-0.005*** (0.002)		-0.005*** (0.001)	
Comparative-advantage industry \times Foreign tariffs (α_2^F)	0.022*** (0.007)		0.024*** (0.006)		0.037*** (0.006)		0.037*** (0.005)	
Swedish tariffs (α_1^S)		0.018 (0.015)	0.022 (0.015)			-0.001 (0.012)	0.005 (0.012)	
Comparative-advantage industry \times Swedish tariffs (α_2^S)		0.008 (0.022)	-0.005 (0.022)			0.016 (0.025)	-0.003 (0.024)	
MNE share (α_1^M)				-0.070* (0.040)				-0.016 (0.032)
Comparative-advantage industry \times MNE share (α_2^M)				0.287** (0.121)				0.256*** (0.091)
F -test: $\alpha_1^F + \alpha_2^F > 0$ (p -value)	<0.001		<0.001		<0.001		<0.001	
F -test: $\alpha_1^S + \alpha_2^S > 0$ (p -value)		0.139	0.235			0.256	0.458	
F -test: $\alpha_1^M + \alpha_2^M > 0$ (p -value)				0.030				0.003
R^2	0.057	0.052	0.062	0.079	0.083	0.054	0.084	0.091
Observations	860	860	860	860	766	766	766	766
Number of industries	88	88	88	88	87	87	87	87

Note : This table examines the robustness of our baseline results to alternative measures of openness. In all regressions the dependent variable is the degree of matching, which is measured as the correlation coefficient between firm total effects and worker total effects. An industry is defined as having a comparative advantage if this industry has positive net export for 1995. 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 Robustness to alternative definitions of trade status

	Positive net exports in 1995	Positive average of net exports	More years with positive net exports	Net exports / (Exports+Imports)
	(1)	(2)	(3)	(4)
Openness (α_1)	-0.001 (0.002)	-0.001 (0.001)	-0.001 (0.001)	0.014*** (0.003)
Comparative-advantage industry × Openness (α_2)	0.022*** (0.007)	0.024*** (0.007)	0.024*** (0.007)	0.035*** (0.007)
<i>F</i> -test: $\alpha_1 + \alpha_2 > 0$ (<i>p</i> -value)	<0.001	<0.001	<0.001	
R^2	0.057	0.059	0.059	0.065

Note : This table examines the robustness of our baseline results to alternative definitions of trade status of an industry. An industry is defined as having a comparative advantage if this industry has positive net export for 1995 in column 1, if this industry has positive average of net exports over the sample period 1995-2005 in column 2, or if this industry has more years with positive net exports in column 3. In column 4 the trade status of an industry is captured by net exports/(exports+imports), which is a continuous measure. Thus, no *F*-test is performed for this case. In all regressions the dependent variable is the degree of matching, which is measured as the correlation coefficient between firm total effects and worker total effects. Openness is measured by foreign tariffs on Swedish exports. 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 7 Robustness to alternative measures of the degree of matching by accounting for match effects

	Baseline	Orthogonal match effects	Hybrid mixed match effects
	(1)	(2)	(3)
Openness (α_1)	-0.001 (0.002)	0.001 (0.002)	0.003* (0.001)
Comparative-advantage industry × Openness (α_2)	0.022*** (0.007)	0.021*** (0.007)	0.016*** (0.007)
<i>F</i> -test: $\alpha_1 + \alpha_2 > 0$ (<i>p</i> -value)	<0.001	<0.001	<0.001
R^2	0.057	0.056	0.058

Notes : In all of the regressions the dependent variable is the degree of matching. See Section 4.E for more details about the measurements of the degree of matching when match effects are accounted for. Openness is measured by foreign tariffs on Swedish exports. An industry is defined as having a comparative advantage if this industry has positive net export 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 8 First-difference regressions for 1995-2005

	Firm effect and worker effect	Firm effect and average worker effect	Firm effect and median worker effect	Capital intensity and worker schooling
	(1)	(2)	(3)	(4)
Δ Openness (α_1)	-0.018 (0.022)	-0.210 (0.107)	-0.191* (0.112)	0.005 (0.017)
Comparative-advantage industry \times Δ Openness (α_2)	0.064*** (0.024)	0.372*** (0.122)	0.346*** (0.128)	0.040** (0.019)
Comparative-advantage industry	-0.133** (0.057)	-0.650** (0.256)	-0.592** (0.268)	-0.070* (0.042)
<i>F</i> -test: $\alpha_1 + \alpha_2 > 0$ (<i>p</i> -value)	0.004	0.004	0.08	<0.001
R^2	0.111	0.141	0.117	0.242
Observations	74	74	74	74

Notes: In all of the regressions the dependent variable is the ten-year difference of the degree of matching over 1995-2005. The degree of matching 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 capital intensity and worker schooling in column 4. Openness is measured by foreign tariffs on Swedish exports. An industry is defined as having a comparative advantage if this industry has positive net export for 1995. There are 74 industries that have data for both 1995 and 2005.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$