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Trade and Wage Distribution Dynamics: When Does Trade Cause the Selection Effect?

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When Does Trade Cause the Selection Effect?

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Abstract

This paper investigates when trade could cause the selection effect. Since the increased average real wage induced by trade triggers the selection effect in Melitz (2003), the main issue is the labor market conditions under which trade raises the average real wage. To identify the labor market conditions for the selection effect, this paper employs worker heterogeneity with respect to abilities in Blanchflower, Oswald, and Sanfey's (1996) rent-sharing framework. This simple model plays a crucial role in building estimation equations that use the residual wage in order to reflect worker heterogeneity. According to the results of regressions of the average and 10th percentile of residual wages, this paper shows that with high union density, low job destruction, and low job creation, the effect of trade on the average residual wage is likely to be negative because the impact of imports exceeds that of exports. Moreover, the impact of trade on the average wage must work through the residual wage because this study does not find a significant impact of trade on the average predicted wage. As a result, the more rigid the labor market is, the less likely trade is to raise the average industrial wage and the less likely the selection effect in Melitz (2003) is to occur.

JEL Classification: F16; J31; C23

I. Introduction

competition as a mechanism to cause the selection effect of trade.[2] Melitz's (2003) argument on the selection effect is that the increase in average real industrial wage induced by exports pushes up the aggregate productivity through taking the least productive firms out of the market. That is, the increased average real wage triggers the selection effect. Surprisingly, despite the critical role of the increased average real wage, little is known about the impact of trade on the average real industrial wage from the viewpoint of aggregate productivity dynamics. Accordingly, the main question that this paper investigates empirically by using U.S. data is as follows: under which labor market conditions does trade raise the average real industrial wage?

Recent theoretical attempts to employ worker heterogeneity in international trade models could help to identify labor market conditions due to explaining firms' and workers' heterogeneous responses to trade. Davidson, decisions. However, how can we handle worker heterogeneity with respect to abilities in an empirical study? Generally, econometricians cannot observe a worker's heterogeneous abilities directly. So there is little empirical evidence despite some theoretical attempts. In this situation, a good alternative is the residual wage stemmed from the Mincerian wage equation because the residual wage reflects the compensation for a worker's ability.[4]

To understand the relationship between abilities and the residual wage, this paper introduces worker heterogeneity with respect to abilities into Blanchflower, Oswald, and Sanfey's (1996) rent-sharing framework. According to this model, the residual wage is determined by a firm's profit and by individual bargaining power that comes from abilities;[5] that is, it reflects the compensation for workers' abilities that are evaluated by a firm. Therefore, although we cannot observe workers' abilities empirically, the residual wage enables us to estimate heterogeneous responses of firms and workers to changes in the compensation for workers' abilities. Particularly, provided that firms' profits and productivities are identified, ability cut-offs in firms can be compared to each other.[6]

How can the residual wage explain the firm's decision to fire and hire workers?

[4] Mincerian wage equation is used to estimate the premium of observed skills such as education and experience. The residual wage is empirically defined by the residual term in Mincerian wage equation. Therefore, it is likely to be connected to unobserved skills that affect the wage. Although the more popular term in studies on residual wage is unobserved skills, this paper uses ability instead of unobserved skills in order to link with theoretical studies on worker heterogeneity.
[5] This is similar to Lemieux (2006)'s assumption that residual wage is the product of abilities and compensation for them because firm's profit is related with firm's ability of compensating for unobserved skills.
[6] Firms with high productivity can cover huge recruiting cost to hire high-ability workers, while unproductive firms cannot afford to pay high recruiting cost. Therefore, unproductive firms are more likely to hire workers with low abilities than firms with high productivity because the adverse effect could be in unproductive firm's recruiting process. Therefore, this paper assumes that the cut-off is closely related to firm's productivity as suggested in Helpman, Itskhoki, and Redding (2009).

When a firm is faced with decreasing profit, it will lay off workers with low residual wages because those workers are evaluated as being less valuable by the firm. In other words, the residual wage reflects how the firm sorts its workers in terms of their performance. Also, in hiring workers to respond to increased market share, the firm would attempt to screen job applicants with abilities below the cut-off. [7] In the case of a worker's decision, the residual wage implies that workers with the same education level and experience could be paid differently according to the firm's profit, which can explain the motivation to search for a better job. If high-ability workers are in an unproductive firm, they would have the motivation to move toward a more productive firm in order to earn more compensation in the individual bargaining. As a result, the firm's and worker's decisions respond to changes in the firm's profit in a rent-sharing framework, which causes job flow.[8]

Trade liberalization affects firms' profits according to their productivity (Melitz, 2003). Thus, as the economy becomes more open to trade, firms and workers would make heterogeneous responses to the changes in the profit, which would determine the average residual wage at the industrial level. These responses suggest two main channels through which trade affects the average residual industrial wage: the change in the firm's profit and job flow. Without considering job flow, the influence on the residual wages of the change in a

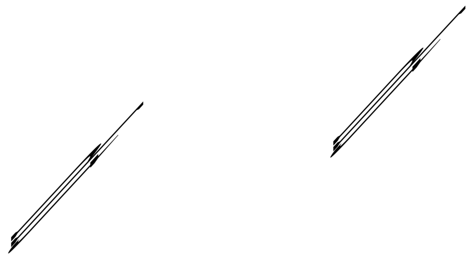
[7] According to Huang and Cappelli (2006), firms can evaluate job applicants' abilities by using popular screening practices such as reference letters and obtaining the agent's past histories through credit bureaus or hiring detectives.

[8] Krueger and Summers (1988) and Gibbson and Katz (1992) focus on the reallocation of workers from low to high wages industries; that is, they examine why workers with the same education level and experience are paid differently in different industries. The residual in this paper explains why the workers move from unproductive firms to more productive firms in the same industry as well as across industries.

firm’s profit from trade is obvious: imports lower the workers’ residual wages because imports make the firm’s market share shrink. In a similar way, exports raise the workers’ residual wages.

However, in considering the job flow, the impact of trade on the average residual wage is more complicated. In the case of exports, the direction of each channel’s impact is removing the negative effect of import on the average (residual) wage without controlling for job destruction.[11] Unlike exports, with imports, the higher the job destruction, the less the residual wage is dispersed.

For empirical work, I use four datasets: Merged Outgoing Rotation Groups Current Population Survey (MORG-CPS), U.S. Trade by Feenstra (1998), Job Creation and Job Destruction by Foster, Haltiwanger, and Kim (2006), and Manufacturing Industry Productivity Database by Bartelsman, Becker, and Gray (2000).[12truc]



wage, this paper runs the regression of the predicted average wage on import penetration and export propensity.[15] According to the results, trade has an insignificant impact. It is expected by the fact that the Mincerian wa

Helpman, Itskhoki, and Redding (2008).[16] This model is simple, but useful in deriving implications for estimation.

Helpman, Itskhoki, and Redding (2008) effectively use the following production function to describe why the firm attempts to screen workers with abilities below the cut-off:

$$y = \theta h^{\gamma} \bar{a} ,$$

This paper also uses screening costs in Helpman, Itskhoki, and Redding (2008). It assumes that if the firm paid a screening cost of , it could screen the workers with abilities below the bargaining power is determined by abilities because the firm takes longer to replace the worker with higher abilities and the firm is likely to earn zero in the event of a bargaining delay. Although the above maximization problem has three choice variables such as , , and , this paper derives the first-order condition with respect to because the introduction of worker heterogeneity makes and the relative bargaining strength between the firm and its individual employee according to an employee's ability; that is, it reflects the compensation for workers' abilities that are evaluated by a firm. This is similar to Lemieux (2006)'s interpretation that the residual wage is the product of abilities with the return to abilities. Therefore, the residual wage implies that workers with the same education level and experience could be paid differently according to the firm's productivity or profit. Moreover, workers with the same education level and experience in the same firm could be paid differently according to their performance.

From equation (4), we can know that the profit and the bargaining power affect the slope in the relationship between the residual wage and abilities. Therefore, we can set up the schedule of the residual wage to abilities in an exporting firm and a non-exporting firm. <Figure 1> shows these schedules in low degree of openness:

<<Figure 1>>

a_c^n is the cut-off point of a non-exporting firm; if a worker had abil

Additionally, an exporting firm will invest more a screening mechanism to identify workers with abilities below the cut-off in order to obtain inside and outside workers with high abilities. That is, due to paying the additional cost such as exporting fixed cost and transportation cost, an exporting firm should be more productive and so need workers with high abilities. Therefore, the cut-off point of an exporting firm (a_c^e) is higher than that of a non-exporting firm.

Through <Figure 2>, we can know how the distribution of residual wage is changed as the economy becomes more open to trade. Higher degree of trade openness in the country where intra-industry trade dominates implies higher import penetration and higher export propensity in the same industry. First of all, the impact of increased import penetration on residual wages is shown by arrows (1) and (2) in <Figure 2>. When import penetration increases, the higher competition in the domestic market requires a non-exporting firm to have workers with higher abilities. Thus, the cut-off of a non-exporting firm increases by $\overline{a_c^n}$.[18] Consequently, the workers with abilities below the new cut-off and the workers in marginal firms will be unemployed. This effect of increased imports (arrow (2)) raises the average residual wage as <Figure 2>. However, there is the other effect of increased imports (arrow (1)). The import penetration also makes the curve of non-exporting firms shift downward because the reduced domestic market share causes decreasing profit. Therefore,

[18] In different way, increased import penetration pushes up the cut-off of a non-exporting firm productivity (θ).

the impact of increased imports on the average residual wage depends on the magnitude of the two effects; that is, *when job destruction below the new cut-off* ($\overline{a_c^n}$) *occurs more, the effect of the shifting downward curve on th* *residual wage also increases*.

The implications derived from this conceptual framework shed an important light on constructing the estimation model in Section 3 and interpreting the results of regressions in Section 4.

III. Data and Estimation Strategy

Data Description

The best way to examine the impact of job flow induced by trade on the average residual wage in section II is to use a ma this data is more reliable than alternative sources of wage data such as March CPS because it provides a less noisy measure of the key variable of interest (compensation per hour). In addition, the CPS-MORG has larger observations than PSID or March/May CPS.

The observable skills such as education and experience are required to obtain the residual wage. When we use schooling as a regressor in wage equations, the CPS has one well-known problem that schooling is not measured in a consistent questionnaire over time; that is, after 1992, a question about the highest graduate attended switched to the highest grade or diploma completed, instead of asking whether the highest grade was completed. Nonetheless, Lemieux (2006) suggests the possible way to construct a relatively consistent variable for years of schooling completed over the whole sample period. In his manner, this paper classifies years of schooli residual wage. In the sample of full-time male workers in the manufacturing sector, the residuals come from separate regressions of the logarithm of real hourly wages on a set of age, a quadratic in age, and nine schooling dummies for each year.[26] <Table 1> is the estimation result of the Mincerian wage equation. The row of Stdev, the standard deviation of coefficients of eight schooling dummies, shows that the inequality among premiums of schooling year is increasing. Particularly, the last row implies that the college premium is also increasing as shown in early literature.[27] In addition, panel (b) in <Figure 3> shows the distribution of full time male workers' residual wages in both 1983 and 1994. Similar to panel (a) in <Figure 3>, the distribution in 1994 is more dispersed.

Furthermore, I draw the cumulative distribution functions for residual wages in several industries in order to capture the impact of import penetration in industries with different labor market conditions. <Figure 4> and <Figure5> show the cumulative distribution functions of residual wages in the industries with a high change rate of import penetration. However, the industries in <Figure 4> have a high change rate of job destruction, while the industries in <Figure 5> are characterized as a low change rate of job destruction.[28] Compared to <Figure 4>, the 1994 residual wage distributions in <Figure 5> are located

[26] Lemieux (2006) uses the interactions between schooling dummies and a quadratic in age in order to improve

wholly in the left of 1983 residual wage distributions. Additionally, the 1994 cumulative distribution functions in <Figure 5> have a longer left-tail than the 1983 ones. These provide suggestive support for the role of arrow (1) and arrow (2) in <Figure 2>. As a result, we can know that a high change rate of job destruction enables an industry exposed to highly increased imports to have fewer workers with low residual wage. Additionally, <Table 2> reports the minimum, average, and maximum values of variables in order to calculate the marginal effects.

Estimation Strategy

This paper introduces the dependent variables such as average and 10th percentile of estimated residual wages at the industry level.[29] These dependent variables also enable us to capture the response of residual wage distribution characteristics to trade. The equation (5) is the starting point in order to capture the impact of imports and exports on the residual wage.

$$Rw_{s,t} = \alpha + \beta_1 Rw_{s,t-1} + \beta_2 uni_{s,t} + \beta_3 \ln imp_{s,t} + \beta_4 \ln \exp_{s,t} + \beta_5 \ln rship_{s,t} + \varepsilon_{s,t} \qquad (5)$$

where $Rw_{s,t}$ is the average, or 10th of the residual wage in the industry s at time t; $uni_{s,t}$ is the union density of industry s at time; $\ln imp_{s,t}$ is the logarithm of import penetration ratio of industry s at time t; $\ln \exp_{s,t}$ is the logarithm of export propensity ratio of

[29] This strategy has an advantage to avoid the Moulton problem. If we construct the estimation equation with individual-level dependent variable and industry-level independent variables, the Moulton problem would make the standard errors underestimated. According to Angrist and Pischke (2009), using group averages instead of microdata is a good way to avoid the Moulton problem.

industry s at time t; $\ln rship_{s,t}$ is the logarithm of real shipment of industry s at time t; $\varepsilon_{s,t}$ is consisted of the s industry-specific effect (ν_s), the time-specific effect (δ_t), and the error-term ($\eta_{s,t}$). In particular, the logarithm of real shipment controls for third factors such as changes in consumer's taste and technology. Therefore, the addition of real industrial shipment enables trade openness in empirical model to be more closely connected with trade liberalization in Melitz (2003).

To answer the main question in this paper, however, we need to modify the equation (5). In the comparison of <Figure 4> with <Figure 5>, we can know the distributional consequence of import penetration on individual residual wages is dependent on the level of job destruction. It gives us the intuition about how to make the empirical equations in order to identify the role of each arrow in <Figure 2>. To reflect this intuition, I modify the equation (5) into (6)-(8) by adding interaction terms with the union density, job destruction and job creation, respectively. However, while running the regression of the 10th percentile of residual wage, I use the equation (5)-(7) to identify the arrow (2) in <Figure 2>.

$$Rw_{s,t} = \alpha + \beta_1 Rw_{s,t-1} + \beta_2 uni_{s,t} + \beta_3 \ln imp_{s,t} + \beta_4 \ln imp_{s,t} * uni_{s,t}$$

$$+ \beta_5 \ln \exp_{s,t} + \beta_6 \ln \exp_{s,t} * uni_{s,t} + \beta_7 \ln rship_{s,t} + \varepsilon_{s,t} \qquad (6)$$

$${}_1 Rw_{s\ t} \quad {}_2 neg_{s,t} \quad {}_3 \ln imp_{s,t} \quad {}_4 \ln imp_{s,t} * neg_{s,t} \quad {}_5 \ln \exp_{s,t} \quad {}_6 \quad {}_{s,t} \quad {}_{s,t}$$

(8)

where $neg_{s,t}$ is the job destruction of industry s at time t; $pos_{s,t}$ is the job creation of industry s at time t.

Although the CPS is the repeated cross-section, I can construct industry-level panel data in order to estimate the equation (5)-(8). Then, the MORG-CPS consists of households in their 4th and 8th interview. So some interviewers are likely to be observed between two years. Since this makes the sample persistent, I use the dynamic panel analysis. The dynamic model permits regressors to include lagged dependent variables, which causes the endogeneity problem.[30] Moreover, the reverse causality between the residual wage and job flow in the equation may occur; that is, the increase of residual wage in exporting firms causes high-ability workers in non-exporting firms to move toward exporting firms voluntarily, which affects job destruction positively. This also engenders the endogeneity problem. Additionally, according to Cameron and Triviedi (2005), the measurement error induces the endogeneity problem in building the industry-level panel data with individual-level data set.

The endogeneity problems presented above suggest the system GMM estimator. The main strength of this estimator is to provide more consistent and efficient estimates in the presence of endogeneity problems.[31] The system GMM estimator is proposed by Blundell

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[30] The fixed effects estimates of the lagged dependent variable can be severely biased downwards for small T as Nickell (1981) shows.

[31] Collado (1997) suggests the GMM estimator in order to remove the endogeneity problem induced by the

and Bond (1998) in order to overcome a significant shortcoming of the first-difference GMM estimator by Arellano and Bond (1991). According to Blundell and Bond, the instruments used with the first-difference GMM estimator become less informative in models where the variance of the fixed effects is high relative to the variance of the transitory shocks. This is called as overfitting biases. Bowsher (2002) shows that the use of too many instruments in GMM estimation causes the p-value of the Sargan test to be close to 1. This implies that the power of the Sargan test can be lost. To correct this problem, this paper restricts instrument in terms of the validity of instruments and the model specification. All three diagnostic statistics in <Table 3-6> are satisfactory; that is, the Sargan test does not reject the over-identification restrictions; the absence of first order serial correlation is rejected while the absence of second order serial correlation is not rejected. Then, I am also concerned with overfitting biases and finite sample bias for the system GMM estimator. To avoid overfitting biases, I do not use any lags dated further back than $t-4$, and so all tables in this paper obtain the Sargan test P-value much smaller than 1. In the case of finite sample bias, Bond (2002) suggests a useful fact: since the OLS and within estimator are biased in opposite directions, the coefficients on the lagged dependent variable estimated by a consistent estimator should lie between the OLS and within estimates. All coefficients on the lagged dependent variable in <Table 3-4> using system GMM are in this interval. This implies that finite sample bias associated with weak instruments is not present. In particular, Windmeijer's (2005) corrected standard error reduces finite sample bias. Therefore, all coefficients estimated by system GMM are consistent without problems.

Looking at column 3 in <Table 3>, the first point to note is that increases in import penetration are associated with decreases in average residual wage, while increases in export propensity are associated with increases in average residual wage. Specifically, an import penetration elasticity of -0.011 in column 3 is significantly different from zero at the 10% level. Also the export propensity elasticity in column 3 is 0.016 and significantly different from zero at the 5% level. And the long-run effect of import penetration and export propensity are -0.044 (SE=0.024) and 0.064 (SE=0.027), respectively.[33 34] That is, the export propensity elasticity is larger than the import penetration elasticity. If the volume of export is similar to that of imports, it implies that trade could raise the average residual wage.

However, the above implication depends on the labor market conditions as suggested in section II. Let's focus attention on column 4-6 in <Table 3a>. In column 4, I attempt to capture the role of the labor market by interacting the union density with import penetration and export propensity, respectively. The column 4 in <Table 3a> shows that the interaction positive as the union density declines. Interestingly, with high union density, the effect of trade on average residual wage is likely to be negative because the impact of imports exceeds that of exports.[35]

<Figure 2> dealt with in section II makes us understand this evidence more clearly. This evidence implies that if the union negatively affects the firm's decision to fire workers below the cut-off, the denser the union would be in increased imports, the more the average residual wage would be affected by the arrow (1) than by the arrow (2) in <Figure 2>. The union tends to preserve jobs through wage concessions. Furthermore, when the union bargains with the firm instead of individual workers, the union is likely to prevent the firm from sorting the workers according to abilities; that is, the firm with a denser union cannot fire the workers with abilities below the cut-off through sorting. Therefore, it dampens the effect of arrow (2) in <Figure 2>. As a result, higher union density in the industry with increased imports is likely to decrease the average residual wage.

Column 5 in <Table 3a> suggests more interesting evidence. Here, I use the index of job destruction in order to capture the impact of arrow (2) in <Figure 2> directly. The interaction term is positive and statistically significant at the 5% level, while import penetration is negative and statistically significant at the 1% level. This result can correspond to <Figure 2> well. Similar to the case of union density, I calculate the marginal effect of

[35] When the union density has the maximum value, the import penetration elasticity is -0.024 and the export propensity elasticity is 0.011. Therefore, -0.024 + 0.011 = -0.013.

import penetration at the minimum, median and maximum values of job destruction. The first column in <Table 3c> shows them. The marginal effects of import penetration increase and change from negative to positive as job destru explained by the arrow (4) in <Figure 2>. Particularly, the second column in <Table 3c> implies that as job creation occurs more, the magnitude of the marginal effect of export propensity is increasing. Particularly, the more job creation happens, the more likely the effect of trade on average residual wage is to be positive because the impact of exports dominates that of imports.[37]

This evidence can be supported by analyzing the workers located in the lowest percentile of residual wage distribution. Thus this paper pays more attention to 10th percentile of residual wage distribution. <Table 4a> shows the results from regression of the 10th percentile of residual wages. Interestingly, the evidence in <Table 4a> shows a similar pattern as <Table 3a>. Specifically, the interaction term between import and job destruction in column 5 is positive and statistically significant at the 1% level, while $\ln import_{s,t}$ is negative and statistically significant at the same level. According to the marginal effect of import penetration in <Table 4b>, the job destruction causes the sizable variation of this marginal effect. That is, the job destruction plays a critical role in raising the 10th percentile of residual wage. If there were the selection effect of import penetration on the workers with ability below the cut-off, the 10th percentile of residual wage would be raised by import penetration. Therefore, as more job destruction occurs, the left-tail of residual wage distribution will be cut. This will push up the average residual wage.

[37] When the job creation has the maximum value, the export propensity is 0.043. The import penetration elasticity in column 6 is -0.015. Therefore, 0.043 - 0.015 = 0.028.

In order to connect those evidences to Melitz (2003) argument, this paper has to examine the impact of trade on the average industrial wage including the average predicted wage and residual wage. Therefore, I turn attention to the impact of trade on the average predicted wage. <Table 5> reports the results from regressions of the average predicted wage on trade. According to column 3 in <Table 5>, import penetration and export propensity are statistically insignificant in the 10% level. We can expect this from the fact that the Mincerian wage equation does not reflect industrial characteristics. In sum, the impact of trade on the average industrial wage is determined only by the residual wage; that is, with high union where $\ln tariff_{s,t}$ is the logarithm of tariff of industry s at time t.[38] However, in the 10^{th} percentile regression, the job creation variables ($pos_{s,t}$ and $\ln tariff_{s,t} * pos_{s,t}$) are excluded because the 10^{th} percentile regression is designed to identify the arrow (2) in <Figure 2>.

According to results, the logarithm of tariffs is negatively but insignificantly associated with the average residual wage. This insignificance could be explained by the fact that since the decreased tariffs are likely to imply the increased imports and increased exports, the impacts of imports on the residual average wage could be offset by that of exports, and vice versa. However, the column 2 in <Table 6a> and the column 1 in <Table 6b> show that as job creation and job destruction are higher, the impact of tariffs on the residual wage is more sizable and significant.

The regression of 10^{th} percentile of residual wages can support these results. The column 3 in <Table 6a> shows that the logarithm of tariff negatively and significantly affects the 10^{th} percentile of residual wages; that is, the lower the tariff is, the higher the 10^{th} percentile of residual wage is. Furthermore, the column 4 in <Table 6a> reports that the interaction term between tariff and job destruction is negative and statistically significant at the 5% level. This interaction term can capture the arrow (2) in <Figure 2>, which implies that the active job destruction is the crucial channel through which the trade liberalization measured by tariffs affects the 10^{th} percentile of residual wage. Specifically, the marginal

[38] The variable of tariff means U.S. import weighted tariffs (duties/custom value). Schott provides this dataset on his website (http://www.som.yale.edu/faculty/pks4/sub_international.htm).

effect of tariffs shows that the magnitude of this marginal effect is increasing as job destruction is high. These results are consistent with the impact of trade openness on the average and 10^{th} percentile of residual wages.

VI. Conclusion

Under which labor market conditions does trade raise the average real industrial wage? This paper shows that with low union density, high job destruction, and high job creation, trade would raise the average real industrial wage. In fact, job creation is closely related with job destruction. According to Scarpetta et al (2002), the employment protection legislation (EPL) prevents new firms from entering the market because of higher firing costs. It is two sides of the same coin. That is, more job destruction can induce more job creation. Therefore, as trade is liberalized more, job turnover is more important in order to work the selection effect of trade in Melitz (2003).

This implication sheds a crucial light on the study about trade and aggregate productivity. Melitz and Ottaviano (2008) and Archaya and Keller (2008) suggest that trade can lower the aggregate productivity under unilateral trade and high entry barriers, respectively. In particular, the high entry barrier in Archaya and Keller (2008) can be connected to the demand of labor, the job creation. Therefore, as suggested in this paper, the labor market condition can be the important link; that is, if the rigidity in the labor market incurs high firing costs, trade would lower the average real industrial wage and the selection effect of trade in Melitz (2003) would never happen. As a result, the more trade increases, the more the labor market conditions matter for aggregate industry productivity dynamics and the worker's long-run welfare.

Reference

Angrist, Joshua D. and Jorn-Steffen Pischke (2009), *Mostly Harmless Econometrics*, Princeton University Press.

Arellano, M. and S. Bond (1991), “Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations,” *Review of Economic Studies*, Vol. 58, pp. 277-97.

Archarya, R.C. and W. Keller (2008), “Estimating the Productivity Selection and Technology Spillover Effects of Imports.” *NBER working paper No. 14079.*

Barlevy, G (2000), “Is there a cleansing effect in recessions? Evidence from wage data.” Manuscript, Northwestern University.

Bartelsman, Eric J., Randy A. Becker, and Wayne B. Gray, (2000), “NBER-CES Manufacturing Industry Database.” NBER and U.S. Census Bureau, Center for Economic Studies.

Blanchflower, David G., Andrew J. Oswald, and Peter Sanfey, “Wages, Profits, and Rent-Sharing.” *The Quarterly Journal of Economics*, Vol. 111, pp. 226-251.

Blundell, R. W. and S. R. Bond (1998), “Initial Conditions and Moment Restrictions in Dynamic Panel Data Models.” *Journal of Econometrics*, Vol. 87, pp. 115-143.

Bond, Stephen (2002), “Dynamic Panel Data Models: A Guide To Micro Data Methods and Practics.” *CeMMAP working paper CWP09/02.*

Bowsher, C. (2002), “On Testing Overidentifying Restrictions in Dynamic Panel Data Model.” *Economics Letters*, Vol. 77, pp. 211-220.

Cameron and Trivedi (2005), *Microeconometrics: Methods and Applications*, New York: Cambridge University Press.

Collado, M. D. (1997), “Estimating dynamic models from time series of independent cross-sections.” *Journal of Econometrics*, Vol. 82, pp. 37-62.

Cunat, Vicent and Maria Guadalupe (2009), “Globalization and the Provision of Incentives inside the Firm: The Effect of Foreign Competition.” *Journal of Labor Economics*, Vol. 27, pp. 179-212.

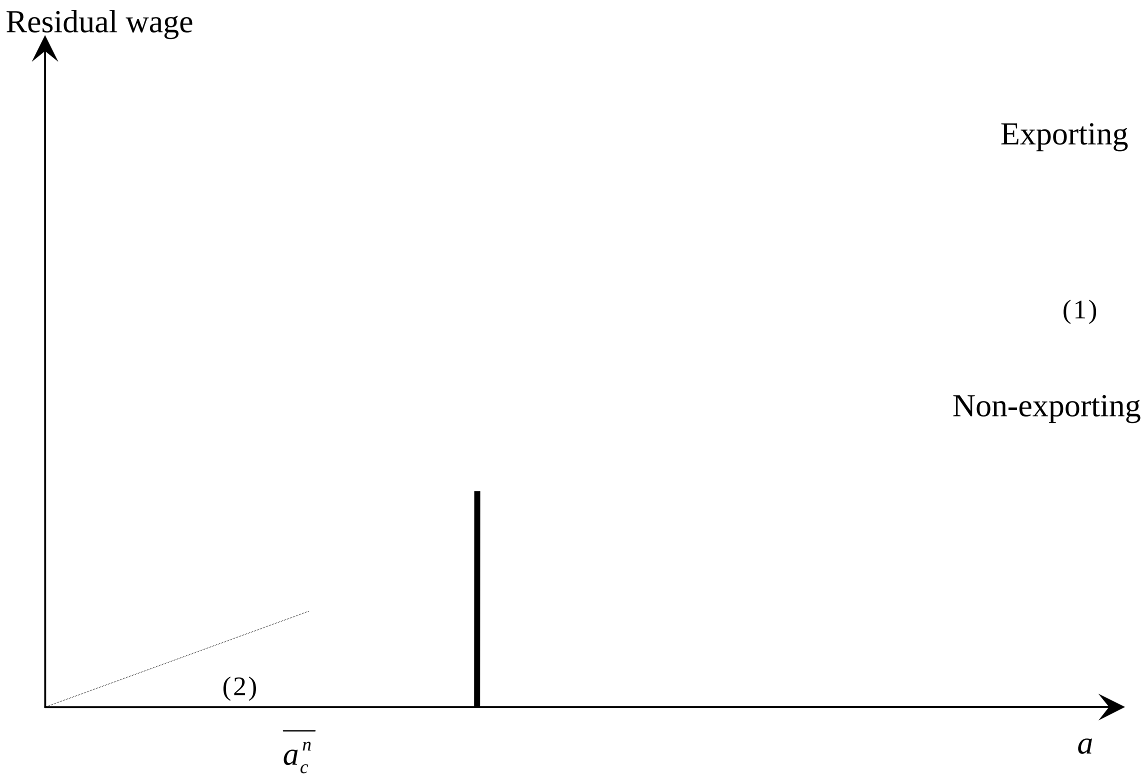
Davidson, Carl, Steven J. Matusz, and Andrei Shevchenko (2008), "Globalization and Firm Level Adjustment with Imperfect Labor Markets." *Journal of International Economics*, Vol. 75, pp. 295-309.

DiNardo, John, Nicole M. Fortin, and Thomas Lemieux (1996), "Labor Market Institutions and the Distribution of wages, 1973-1992: A Semiparametric Approach." *Econometrica*., Vol. 64, pp. 1001-1044.

Ebenstein, Avraham, Ann Harrison, Margaret McMillan and Shannon Phillips (2009),

<Figure 1> The schedule of the residual wage to abilities in low degree of trade openness

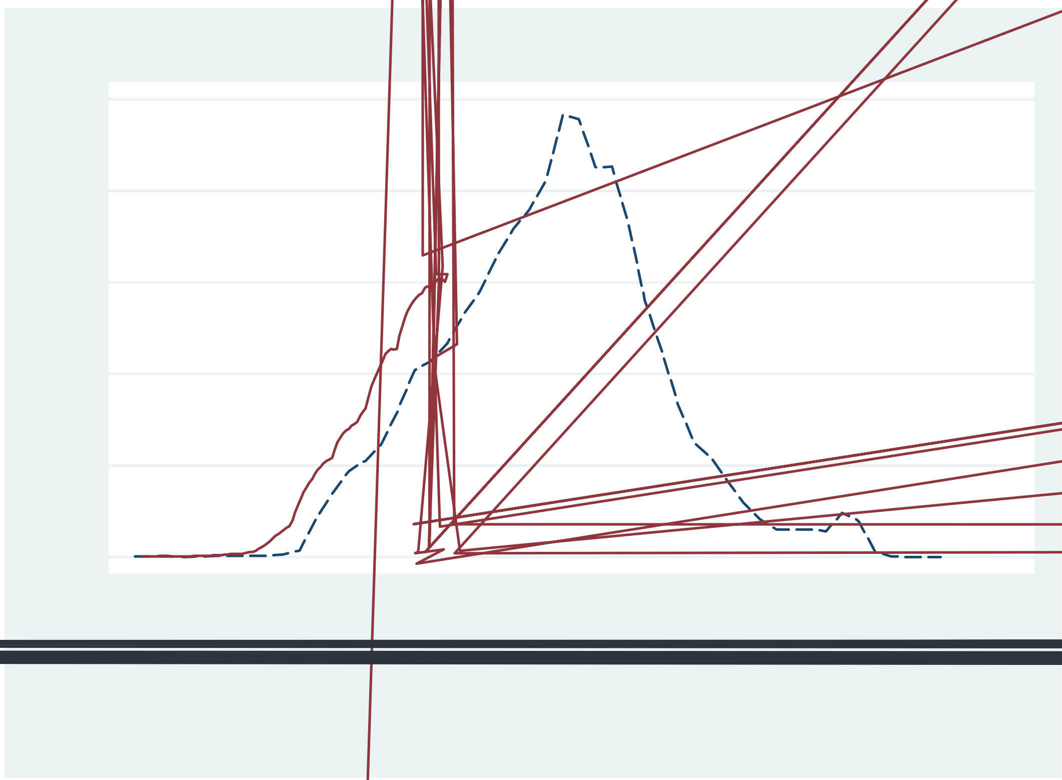
<Figure 2> The schedule of the residual wage to abilities in higher degree of trade openness



Notes: a_c^n is the cut-off of non-exporting firm. a_c^e is the cut-off of exporting firm.

<Figure 3> The distribution between 1983 and 1994 in the manufacturing sector

Panel (a): real hourly wage



<Table 1> Regression results of a Mincerian equation.

	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994
Exp	0.065	0.065	0.066	0.067	0.064	0.064	0.063	0.061	0.06	0.06	0.061	0.063
Exp2	-0.0006	-0.0006	-0.0006	-0.0006	-0.0006	-0.0006	-0.0006	-0.0006	-0.0006	-0.0006	-0.0006	-0.0006
ed2	0.157	0.172	0.173	0.228	0.194	0.143	0.076	0.093	0.087	0.131	0.104	0.114
ed3	0.269	0.25d[(06c39]TJEMC	/P	<</MCID	52	>>BDC	90TJEMC70.)7(17)6(3)6(	)	<</MCID			

<Table 3a> Regression results: Dependent variable = Average residual wage

	OLS	Within	SYS-GMM	SYS-GMM	SYS-GMM	SYS-GMM
$Rwage_{s,t-1}$	0.846***	0.231***	0.755***	0.737***	0.785***	0.772***
	(0.019)	(0.071)	(0.079)	(0.086)	(0.084)	(0.087)
$\ln ship_{s,t}$	0.0024	0.0069	0.0031	0.0048	0.00021	-0.0038
	(0.0021)	(0.025)	(0.0036)	(0.0079)	(0.0075)	(0.0068)
$uni_{s,t}$	0.023*	0.091**	0.125	0.00034		
	(0.013)	(0.044)	(0.088)	(0.108)		
$neg_{s,t}$					0.0020	
					(0.0021)	
$pos_{s,t}$						0.0052
						(0.0039)
$\ln import_{s,t}$	-0.0035*	-0.0051	-0.011*	0.0091	-0.039***	-0.015*
	(0.0018)	(0.0078)	(0.0062)	(0.0099)	(0.014)	(0.0078)
$\times uni_{s,t}$				-0.053*		
				(0.028)		
$\times neg_{s,t}$					0.0019**	
					(0.00089)	
$\ln export_{s,t}$	0.0043**	0.0101*	0.016**	0.0034	0.021**	0.0027
	(0.0019)	(0.0053)	(0.0060)	(0.015)	(0.0083)	(0.0065)
$\times uni_{s,t}$				0.012		
				(0.040)		
$\times pos_{s,t}$						0.0015*
						(0.00086)
R2 / Time	0.811/O	0.693/ O	./ O	./O	./O	./O
Obs.	814	814	814	814	814	814
AR(1)/AR(2)	/	/	0.00/0.599	0.00/0.569	0.00/0.466	0.00/0.471
Sargan			0.712	0.850	0.786	0.691

Notes: [a]: Robust standard errors are reported in brackets. Significant variables at 10%, 5%, and 1% significance level are marked with *, **, and ***, respectively. [b]: The standard errors in Within are corrected using a bootstrapping procedure. [c]: This system-GMM uses lags up to *t*-4 as instruments to avoid overfitting biases.

<Table 3b> Marginal effects of import penetration and export propensity in column 4

	Import	Export
Min	0.0078(0.0093)	0.0037(0.014)
Median	-0.0032(0.0068)	0.0063(0.0074)
Max	-0.024(0.013)*	0.011(0.012)

Notes: Standard errors are calculated by delta method and reported in brackets. Significant variables at 10%, 5%, and 1% significance level are marked with *, **, and ***, respectively.

<Table 3c> Marginal effects of import penetration in column 5 and export propensity in column 6

	Import	Export
Min	-0.036(0.013)***	0.0047 (0.0060)
Median	-0.022(0.0079)***	0.015 (0.0065)**
Max	0.030(0.022)	0.043 (0.020)**

Notes: Standard errors are calculated by delta method and reported in brackets. Significant variables at 10%, 5%, and 1% significance level are marked with *, **, and ***, respectively.

<Table 4a> Regression results: Dependent variable = 10th-percentile residual wage

	OLS	Within	SYS-GMM	SYS-GMM	SYS-GMM
$Rw_{s,t-1}$	0.644***	0.017	0.300**	0.317**	0.511***
	(0.041)	(0.054)	(0.147)	(0.153)	(0.168)
$\ln rship_{s,t}$	0.0077*	-0.0078	0.012	0.020	0.0069
	(0.0045)	(0.076)	(0.015)	(0.022)	(0.019)
$uni_{s,t}$	0.124***	0.201***	0.368*	-0.055	
	(0.030)	(0.059)	(0.214)	(0.285)	
$neg_{s,t}$					0.00003
					(0.0037)
$\ln import_{s,t}$	-0.0056	0.00020	-0.0047	0.0091	-0.059***
	(0.0040)	(0.0095)	(0.013)	(0.021)	(0.015)
$\times uni_{s,t}$				-0.092*	
				(0.055)	
$\times neg_{s,t}$					0.0033***
					(0.0013)
$\ln export_{s,t}$	0.0098**	0.011	0.029**	0.030*	0.057***
	(0.0040)	(0.0071)	(0.015)	(0.017)	(0.016)
R2 / TimeDummy	0.564/O	0.140/O	./ O	./O	./O
Obs.	814	814	814	814	814
AR(1)/AR(2)	/	/	0.01/0.209	0.005/0.219	0.00/0.132
Sargan			0.384	0.398	0.762

Notes: [a]

<Table 5> Regression results: Dependent variable = Average predicted wage

	OLS	Within	SYS-GMM
$Rw_{s,t-1}$	0.945(0.017) ***	0.292(0.051)***	0.893(0.050)***
$\ln rship_{s,t}$	0.0031(0.002)	0.024(0.038)	0.0041(0.0024)*
$uni_{s,t}$	-0.0017(0.0090)	-0.0047(0.027)	0.052(0.087)
$\ln imp_{s,t}$	-0.00094(0.0014)	-0.0064(0.0062)	-0.004(0.007)
$\ln \exp_{s,t}$	0.0013(0.0014)	0.00087(0.0049)	0.0090(0.0061)
R2 / TimeDummy	0.894 / Yes	0.622 / Yes	. / Yes
Obs.	814	814	814
AR(1) / AR(2)			0.00 / 0.516
Sargan			0.399

Notes: [a]: Robust standard errors are reported in brackets. Significant variables at 10%, 5%, and 1% significance level are marked with *, **, and ***, respectively. [b]: The standard errors in Within are corrected using a bootstrapping procedure. [c]: This system-GMM uses lags up to *t*-4 as instruments to avoid overfitting biases.

<Table 6a> Regression results of Tariff: Dependent variable = Average residual wage and 10th-percentile residual wage

Dependent variable	Average	Average	10th	10th
	SYS-GMM	SYS-GMM	SYS-GMM	SYS-GMM
$Rwage_{s,t-1}$	0.829*** (0.060)	0.858*** (0.074)	0.463*** (0.132)	0.473*** (0.106)
$\ln rship_{s,t}$	0.0043** (0.0021)			