TRADE AND TURNOVER: THEORY AND EVIDENCE*

Carl Davidson and Steven J. Matusz

Michigan State University

Initial Draft: June 2001

This Version: October 2002

Is the pattern of trade correlated with cross-sector differences in job turnover? Theoretically, cross-sector differences in turnover give rise to compensating wage differentials, which feed through to output prices. Cross-country differences in turnover are an independent factor in determining comparative advantage. Using two different data sets on turnover, we find strong evidence that normalized U.S. net exports by sector are negatively correlated with job destruction and worker separation rates. Weaker evidence suggests a positive correlation with between normalized net exports and job acquisition. Using sector-specific job destruction data for both Canada and the U.S., we find confirmation of the theoretical prediction that normalized net exports to Canada are negatively related to the ratio of the U.S. job destruction rate to the Canadian job destruction rate.

---

* We owe a great debt to numerous people who provided us with many detailed and thoughtful comments at various stages of this research. In particular, we would like to thank Mary Amiti, John Giles, Daniel Hamermesh, James Harrigan, David Hummels, Christopher Magee, Douglas Nelson, Peter Schmidt, Richard Upward, Katharine Wakelin and Jeffrey Wooldridge. We would also like to thank seminar participants at the Upjohn Institute for Employment Research, the Spring 2001 meeting of the Midwest International Economics Group, Michigan State University, the University of Nottingham, and the Fall 2001 meeting of the EIIT conference at Purdue University.

1. Introduction.

The seminal work of Steven Davis and John Haltiwanger (1992) and Davis, Haltiwanger and Scott Schuh (1996) provides a detailed and rich picture of job creation and destruction within the U.S. manufacturing sector.[1] Among the many interesting findings presented by these authors, two are particularly salient for what follows. First, the rates of job creation and destruction vary widely across manufacturing sectors. Job destruction rates range from a low of 6.8 percent (paper) to a high of 14.4 percent (apparel). The average job destruction rate during this period of time was 10.3 percent with a standard deviation of 1.9 percentage points. Qualitatively similar numbers characterize the dispersion of job creation rates.[2] Labor market turnover can also be quantified based on worker flows. Until 1981, the United States Bureau of Labor Statistics (BLS) compiled and published data on worker turnover by industry. The picture that emerges from this data is qualitatively similar to that portrayed by the DHS job turnover data. For example, in 1981 (the last year for which this data is available), the job separation rate varied from a low of 2.3 percent (instruments and related products) to a high of 5.8 percent (food and kindred products). The (unweighted) average separation rate for this year was 3.9 percent with a standard deviation of 1.1 percentage points. Again, similar properties characterize worker accession rates.

Secondly, DHS allude to comparable measures of job creation and destruction in countries other than the United States. Since this is not the focus of their research, DHS do not present a detailed tabulation of job turnover rates by industry and country, but perusal of Table 2.2 in DHS makes it clear that there is wide variation across countries in overall job creation and

---

[1] Since we frequently refer to their work, we subsequently use the abbreviation DHS to cite their 1996 book.

[2] See Table 3.1 in DHS for the stylized facts referenced in this paragraph. The job creation and destruction rates are measured as the numbers of new jobs created or destroyed between one year and the next as a percentage of the average number of jobs existing in the two years.

destruction rates. For example, one study estimates a 7.7 percent average rate of job destruction in Germany. At the other extreme, the estimated average rate of job destruction in New Zealand is close to 20 percent.[3] This evidence on cross-country differences in turnover rates nicely complements the recently growing literature on cross-country differences in labor market institutions. A variety of authors have pointed out that countries differ considerably in union coverage rates, laws governing the hiring and firing of workers, the generosity of publicly provided social insurance, the type and extent of publicly supported training programs, and other factors that help determine the flexibility of the labor market (see, for example, Richard Freeman 1994, Lars Ljungqqvist and Thomas Sargent 1998, and Daron Acemoglu and Jorn-Steffen Pischke 1999). As a result, it is by now widely accepted that there is a substantial difference in the institutional structure of labor markets across countries.

The apparent differences in labor market turnover rates across industries and countries suggests that these turnover rates could provide an independent determinant of comparative advantage and should therefore be correlated with observed patterns of trade. The intuition underlying this assertion is based on one of the main lessons from general-equilibrium trade theory -- that comparative advantage is the result of the interaction of intersectoral differences with cross-country differences. In the Ricardian model, comparative advantage arises because labor productivity differs between countries and (for at least one country) between sectors. Comparative advantage in the Heckscher-Ohlin-Samuelson model is the result of cross-sector differences in factor intensities combined with cross-country differences in factor supplies.

[3]A recent search of the Social Sciences Citation Index uncovered 128 articles that reference Davis and Haltiwanger (1992). Many of these articles use the DHS methodology to examine job creation and destruction in other countries. Examples include David Blanchflower and Simon Burgess (1996), Jeff Borland (1996), Karsten Albaek and Bent Sorensen (1998), John Baldwin, Timothy Dunne, and Haltiwanger (1998), Valentijn Bilsen and Jozef Konings (1998), Yuji Genda (1998), John Abowd, Patrick Corbel, and Francis Kramarz (1999), and Clement Chow, Michael Fung, and Ngo Hang Yue (1999).

In a recent paper with Lawrence Martin (Davidson, Martin, and Matusz 1999) we provided a detailed theoretical model to precisely explain how labor market turnover rates that vary by industry and country are linked to relative production costs and, therefore, the pattern of comparative advantage. In that paper we examined a model of a two-sector economy that incorporated labor market turnover.[4] In particular, we assumed that unemployed labor required time to find suitable employment. Once found, a job would last until a random shock resulted in a separation, at which time the worker would once again be unemployed. In that model, we allowed the job breakup rates and job acquisition rates to differ across sectors and across countries.[5] Using b_i to denote the breakup rate in sector *i* and e_i to denote sector *i*'s rate of job acquisition, we showed that p_i, the price of the good produced in sector *i*, is an increasing function of b_i and a decreasing function of e_i. The intuition for this result is akin to that of a compensating wage differential. Holding all other factors constant, sectors that have relatively high breakup rates need to pay higher wages to encourage prospective employees to accept jobs within that sector rather than in a sector where jobs are more secure. Similarly, jobs that are relatively difficult to obtain (that is, where e_i is relatively small) need to offer a wage premium to induce prospective employees to undertake the time and effort needed to obtain a job in that sector rather than another sector where jobs are easier to obtain. Abowd and Ashenfelter (1981) find empirical support for the proposition that inter-industry wage differentials compensate for differences across industries in the risk of unemployment. In their work, they assume that a worker can choose to accept a job in a sector where there is no constraint on labor supply, or accept employment in a sector where labor supply is constrained. They assume that the expected

[4] We also allowed simultaneously for turnover in capital markets, but the results are identical and the exposition is simpler if we focus our discussion here on labor markets.
[5] Technically, acquisition rates were endogenous, but we specified an acquisition technology that incorporated an exogenous parameter which differed by sector and by country.

value of the constraint is known, but the actual constraint is random. In an equilibrium, worker indifference between the two sectors implies that the constrained sector must pay a higher wage. The authors use data from the Panel Study of Income Dynamics (1967-1975) to estimate the effect of unemployment uncertainty on the wage differential. They conclude that the compensating differentials ranged from less than one percent in industries where there was relatively little anticipated unemployment, to as much as fourteen percent in industries where there was a relatively large amount of anticipated unemployment.

The implication for trade theory is that a country has a comparative advantage in sectors where the breakup rate is low and/or the job acquisition rate is high relative to the same sector in other countries.[6] Our intent in this paper is to use available data on job turnover, worker turnover, and trade patterns to see if we can find support for our theoretical findings. To preview our results, we do indeed find strong evidence that higher rates of job destruction or worker separations are associated with a smaller level of net exports.[7] This correlation emerges from the data even after controlling for other variables that are likely to be associated with the volume and pattern of trade. We also use job creation and worker accessions to create a proxy for the job acquisition rate. While we do find that our proxy for job acquisitions is positively correlated with net trade, the correlation is not as strong as that relating net trade with job destruction or worker separations. As we note in our discussion of the data, our proxy for the job acquisition rate only loosely approximates the theoretical counterpart. By contrast, both the job destruction

[6] This would seem to imply that export industries are characterized by relatively low wages while import-competing industries are characterized by high wages. Given the strong evidence to the contrary in the United States, it would appear that this is *prima fascia* evidence against the model. However, this would be a misinterpretation of the model. In particular, each category of labor (skilled, semi-skilled, unskilled, and so on) has to be compensated for increased job risk, but this will not impinge on the rank ordering of wages across skill groups. Since U.S. exports are relatively intensive in the use of high-skilled labor, average wages will be higher than in import-competing industries.

[7] Of course, we normalize our trade variables to account for size variation across sectors.

rate and the job separation rate are reasonably good proxies for the breakup rate that shows up in the theoretical model.

It is perhaps worth noting that we might expect turnover to exert an independent influence on the costs of production, and hence on the pattern of comparative advantage, even in the absence of the general-equilibrium effects that were formally modeled in Davidson, Martin, and Matusz (1999). The reason is that turnover itself is costly. Presumably, firms need to expend resources to train newly hired employees and to find and recruit replacements for those who leave. Holding all else constant, higher turnover is more costly.

The logic of our model has the cause-and-effect running from turnover rates to trade patterns. It is, however, quite easy to envision the causality running in the other direction. One might argue that a surge of imports causes job destruction while a burst of exports is likely to create new jobs. According to this argument, *changes* in trade flows (not levels of trade flows) cause *changes* in turnover rates.[8] We are sensitive to this interpretation and take care in our empirical work to try to sort out the direction of causality. As we show, the data provides significantly more support for causality running from turnover to trade than it does for the reverse causality.

Before discussing the data and presenting our results, we note that that our work is related to the recently growing literature in which a variety of authors have argued that cross-

[8] Such an argument seems to be widely embraced by the public and many in the policy community. In fact, it is likely that this is the implicit reasoning that lies behind political debates regarding the impact of trade on employment. The extent to which such arguments are utilized should not be minimized. Robert Baldwin and Christopher Magee (2000) report that 239 members of the United States House of Representatives chose to make brief statements explaining their planned vote on the adoption of the North American Free Trade Agreement. Of those in favor of NAFTA, 70 percent cited the perceived impact on jobs and wages as the most important reason for their vote. Among those opposed to NAFTA, a plurality (44 percent) also cited the perceived impact on jobs and wages as the most important reason for their vote. In personal discussions with Magee, we were told more explicitly that of the 141 anti-NAFTA statements made, 112 were of the form "NAFTA will destroy jobs," while 199 of the 219 pro-NAFTA statements made were of the form "NAFTA will create jobs." Nevertheless, in spite of the widespread support for such views in the public domain, academic economists tend to dismiss such concerns. Moreover, as far as we know, to date no one has provided any empirical evidence that supports the view that changes in trade patterns affect labor market turnover.

country differences in labor market structure can have interesting and important implications for a host of issues. For example, Richard Layard, Stephen Nickell, and Richard Jackman (1991) have investigated the implications of such differences for macroeconomic stability while Richard Freeman (1994) has explored how such differences affect the pattern of job training. Paul Krugman (1994) has argued that the different manner in which recent changes in technology and trade patterns have filtered through economies can be linked to the differences in their labor market structures. He points out that the United States, with its flexible, high turnover labor market has been characterized by a dramatic change in the distribution of income while European countries, with their rigid, relatively low turnover labor markets, have been characterized by a dramatic increase in unemployment among low skilled workers. Donald Davis (1998) makes a similar point when he shows how countries with downwardly rigid wages may be insulated from trade shocks if their trading partners have flexible labor markets that allow them to absorb such shocks.[9] Our theory pushes this logic in a new direction, arguing that labor market structure can affect the pattern of trade across countries.

We describe our data and discuss how well it matches our conceptual framework in the following section. We report our results in Section 3. We summarize and provide some concluding remarks in Section 4.

[9] See also the recent paper by Olivier Blanchard and Augustin Landier (2001) who relate turnover (a labor market outcome) with French institutional reform undertaken in the 1980s that provided firms with wider leeway in hiring workers under fixed term contracts (rather than standard contracts of indefinite term). In turn, this has allowed firms more flexibility in terminating workers since firms are permitted to more easily terminate workers who were employed on fixed term contracts. However, firms are subject to a substantially higher level of firing costs in the event that workers are kept on beyond the duration of the contract. Blanchard and Landier argue on theoretical grounds that this sort of policy could set up perverse incentives for firms to terminate workers on fixed term contracts even when the quality of the match appears good, thus creating higher turnover. They provide empirical evidence that this has indeed been the case.

2. The Data.

As indicated in the introduction, we make use of two distinct sets of data on labor market turnover. The purpose of this section is to describe this data and discuss the conceptual fit between the data and the theoretical underpinnings of the model presented in Davidson, Martin, and Matusz (1999). [10]

The data underlying the statistical analysis of job creation and destruction undertaken by DHS is the Longitudinal Research Database (LRD) that was developed by the United States Census Bureau. While the original establishment-level data is not available for public use, DHS have aggregated the data to the sectoral level and made these data freely available for anyone to use.

The LRD combined data from the quinquennial census of manufactures with annual survey data to ascertain, *inter alia*, establishment-level employment numbers.[11] The survey asks respondents to list the number of employees (both full time and part time) on the payroll as of a specified pay period in March of the designated year. Since the same establishments were surveyed every year, DHS were able to track plant-level employment changes.[12]

To generate job creation and job destruction data for any particular grouping of establishments (for example, by SIC) for year t, DHS first divide the entire set of establishments into three groups. The first group includes all of those establishments that had more employees on the payroll in March of year t than they did in March of year $t-1$. Call this set of establishments S^{+}. The second group includes all of those establishments that had fewer employees on the payroll in March of year t than they did in the previous March. The set of

[10] Of course the authoritative (and complete) description of the DHS dataset is provided in the Appendix to their book.
[11] In this context, an establishment is a plant employing (generally speaking) five or more workers.
[12] Establishments rotated in and out of the sample at 5-year intervals.

establishments in this group is denoted by S^-. Of course the remaining establishments (presumably accounting for only a very small share of overall manufacturing employment) constitute the set of establishments for which there was no change in employment.

Considering only those establishments in the set S^+, DHS define the gross number of new jobs created as the sum of all employment increases between year *t-1* and year *t*. To convert this into a job creation *rate*, DHS divide by the average aggregate employment level of all firms in sector *S* between *t-1* and *t*. That is, if N_{et} represents employment at establishment *e* in March of year *t*, and if C_{st} represents the gross number of jobs created in sector *S*, then

$$(1) \qquad C_{st} = \sum_{e \in S^+} \left(N_{et} - N_{e,t-1} \right)$$

$$(2) \qquad c_{st} = \frac{C_{st}}{\frac{1}{2} \sum_{e \in S} \left(N_{et} + N_{e,t-1} \right)}$$

where the lower case letter refers to a rate, while the upper case letter refers to a level.

While this job creation variable is certainly very interesting for many purposes, it is not what we have in mind by the job acquisition parameter represented by e_i in the introduction of this paper. The problem is that it does not really tell us how easy or hard it is for an unemployed worker to find a job in a particular sector, nor does it tell us how easy or hard it is for a firm with vacancies to find appropriate employees. Expanding establishments may hire many workers relative to their existing employment base, yet this may only be a small fraction of the workers who are looking for a job in that sector, implying that it is relatively easy for firms to find workers, but difficult for the unemployed to find jobs. Similarly, a small job creation rate could possibly be associated with a small pool of workers looking for employment in that sector, and therefore correspond to relatively easy entrée into the sector, but possibly higher costs of recruiting. Even so, it is possible to use this measure to tease out an expression that has some bearing on the issue at hand.

The supply of new jobs created by firms in sector *S* relative to the aggregate number of new jobs created by manufacturing firms in all sectors combined provides some sense of the relative magnitude of job creation emanating from sector *S*. That is, a sector could have a relatively low job creation rate but be responsible for the lion's share of new jobs created in the manufacturing sector if that sector accounts for a relatively large portion of base employment. To calculate our proxy of the job acquisition rate, which we denote by $\tilde{e}_{it}$, define λ_{it} as the share of total manufacturing employment in year *t* accounted for by sector *i*. The employment-weighted average job creation rate in year *t* is then[13]

$$(3) \qquad c_t = \sum_i \lambda_{it} c_{it} \ .$$

Furthermore, the share of jobs accounted for by sector *j* is simply

$$(4) \qquad \tilde{e}_{jt} = \frac{\lambda_{jt} c_{jt}}{c_t} .$$

We shall refer to $\tilde{e}$ as the job acquisition rate in the remainder of this paper. However, we note here that the measure represented by (4) is not a perfect proxy for the true job acquisition rate, since we know nothing about the pool of workers suited for employment in different sectors. For example, some sectors are intensive in the use of skilled labor; others are intensive in the use of unskilled labor. It may be that $\tilde{e}$ is relatively small for a sector that uses highly skilled labor. However, if the pool of qualified workers is also small, it may not be all that difficult to obtain employment in this sector.

[13] DHS report the annual employment-weighted job creation rates for the U.S. in Table 2.1.

The DHS measure of job destruction is calculated in a manner analogous to the job creation rate. However, this measure is much closer to our concept of the breakup rate, represented by b_i, that is pivotal in our theoretical model. To emphasize the similarity, we depart from the DHS notation to use the symbol B_{st} to represent the gross number of jobs destroyed between period $t-1$ and period t.[14] Then by definition

$$B_{st} = \sum_{e \in S^-} \left| N_{et} - N_{e,t-1} \right| \tag{5}$$

$$b_{st} = \frac{B_{st}}{\frac{1}{2} \sum_{e \in S} \left(N_{et} + N_{e,t-1} \right)}. \tag{6}$$

While the DHS data captures annual changes in the number of jobs at an establishment, the BLS data focuses squarely on worker accessions and separations. Labor market turnover as reported by the United States Bureau of Labor Statistics represent the gross movement of workers into (accessions) and out of (separations) employment at the level of individual establishments. This data was reported in Table D-2 of *Employment and Earnings* until 1981, when collection of this data ceased because of budgetary reasons.[15] To see the difference between job flows and worker flows, note that an establishment might experience a 10 percent separation rate during the course of the year (due to retirements, quits, or layoffs) at the same time that it has a 10 percent accession rate (consisting of new hires and rehires). This establishment would end the year with the same number of employees as it had at the beginning of the year, and would therefore not exhibit any job creation or destruction, yet turnover would be substantial. Turnover in the DHS data requires heterogeneity between establishments, while

[14] DHS use D_t to represent this variable.

[15] The BLS data was classified according to 1967 SIC codes prior to 1978, and discontinued after 1981. Note, however, that the 1981 data is reported in the March 1982 issue of *Employment and Earnings*.

turnover in the BLS data may exist due to heterogeneity of worker experience within establishments.[16]

The BLS measure of job accessions is subject to the same weakness as the DHS measure of job creation is vis-à-vis the match with the theoretical model. Therefore we handle this variable in the same way that we handle the DHS measure of job creation. That is, we construct a proxy for job accession that for each industry is the job accession rate multiplied by the industry's share of manufacturing employment relative to the average accession rate in manufacturing.

Both sets of turnover data are reported at the 2-digit and 4-digit SIC level (based on the 1972 revision to SIC codes). However, the DHS data encompasses 447 4-digit industries per year, while the BLS data only covers 106 such industries. The DHS data is available for the years 1973-1986, while the BLS data is available for the years 1978-1981.

In order to look for a correlation between job turnover and trade patterns, we combine the DHS and BLS datasets with data on U.S. trade that was compiled by Robert Feenstra and made available from the National Bureau of Economic Research.[17] To control for a variety of industry-specific characteristics that could be associated with both job destruction and trade patterns, we also use data from the NBER Manufacturing Productivity Database.[18]

3. Empirical Results.

Before turning to our own results, we would be remiss if we did not mention the fact that DHS also inspected their data to see if there was a correlation between job turnover and trade.

---

[16] See Davis and Haltiwanger (1998) for a lucid discussion of the differences between worker flows and job flows, along with a description of the available data for each.

[17] See Feenstra (1996, 1997) for a description of the trade data.

[18] This data is maintained by Eric Bartelsman, Randy Becker, and Wayne Gray and is available from the National Bureau of Economic Research. A description of this data is provided in Bartelsman and Gray (1996).

They conclude, based on a perusal of Table 3.5 in their book, that "(there is) no systematic relationship between the magnitude of gross job flows and exposure to international trade." The table on which they base their conclusion is simply a cross-tabulation, dividing industries into quintiles (based on import penetration ratios on the one hand, or the share of output devoted to exports on the other) and then reporting the weighted average job destruction and job creation rates of 4-digit SIC sectors within each quintile. While this examination might be a sensible first pass at the data, it is certainly incomplete. In the first instance, it throws away an amazing amount of information by distilling 14 years of data with nearly 450 observations per year into just 5 averages. In any event, even Davis, Haltiwanger and Schuh acknowledge that the evidence that they present regarding trade and turnover is "crude" and note that "a more careful and extensive study might reveal an important connection between international openness and the degree of job security."[19] To our knowledge, we are the first to undertake this type of analysis.

In order to explore more thoroughly the possible connection between labor market turnover and trade patterns, we must first choose a way to measure the degree to which an industry is engaged in international trade. To this end, we represent our measure of net exports in industry *i* at time t by T_{it} and calculate it as

$$(7) \qquad T_{it} = \frac{E_{it} - M_{it}}{Q_{it} + M_{it}} \times 100$$

where E_{it} , M_{it}, and Q_{it} represent gross exports, imports, and production attributed to sector *i* during year *t*. This measure ranges between +100 (if there are no imports and if all output is

[19] See DHS, p. 175.

exported) to –100 (if there is no domestic production and no re-export of imports).[20] The intuition that we provided in the introduction to this paper loosely suggests that the United States should have a comparative advantage in industries with relatively high job acquisition rates and relatively low job destruction rates.[21] Therefore, we might expect to see a positive correlation between our proxy for the job acquisition rate and the trade index, and observe a negative correlation between job destruction rates and the trade index.

The scatter diagrams in Figures 1 and 2 represent our first crude look at the data. Each observation in these diagrams represents one 2-digit manufacturing industry for a particular year (1973-1986). With twenty 2-digit manufacturing industries per year, there are a total of 280 observations. The slopes of the OLS regression lines in Figures 1 and 2 have the expected signs. Moreover, the slopes are both large in magnitude and highly statistically significant.[22] Figures 3 and 4 show similar relationships when we use the BLS measures of worker turnover rather than the DHS measures of job turnover. Once again, there are twenty 2-digit industries per year, but there are only 100 total observations since the data is only available on a 1972 SIC basis from 1977-1981. From these figures, it is evident that the trade index is negatively correlated with worker separations. Moreover, this relationship is large in magnitude and statistically

[20] The qualitative nature of our results are substantially unaffected if instead we were to use either import penetration or exports as a share of output as our dependent variable.

[21] This is only a loose interpretation since what really matters for the pattern of trade is differences in the pattern of job destruction rates *across countries*. Our data only applies to the United States, so we do not have a direct test of this hypothesis. We return to this issue in the conclusion of the paper.

[22] The slope coefficient in Figure 1 has a value of –0.68 and an associated *t*-statistic of –6.2. The slope coefficient in Figure 2 has a magnitude of 0.68 and an associated *t*-statistic of 4.9. The average absolute value of the trade index in this sample of two-digit industries is 5.8. The average job destruction rate from 1973-1988 is 10.3 (see Table 2.1 of Davis, Haltiwanger, and Schuh (1996)) and the average value of $\tilde{e}$ is 5.0 (there are 20 industries, so each accounts on average for five percent of the newly created jobs). Evaluated at the sample mean, the elasticity of the trade index with respect to the job destruction rate implied by Figure 1 is –1.2 and the elasticity of the trade index with respect to the job acquisition proxy implied by Figure 2 is 0.6. Moreover, values of $\overline{R}^2$ for the regressions corresponding to Figures 1 and 2 are 0.12 and 0.08, respectively.

significant.[23] Figure 4 shows that when we use job accessions in our formula for the proxy of the job acquisition rate, the relationship between the trade index and proxy of job acquisitions is positive, but weak. In fact, the slope coefficient is statistically insignificant, and variations in the proxy of job acquisitions accounts for less than one percent of the variation in the trade index.[24]

The empirical relationship between the trade index and job turnover is robust to a variety of changes in the way that the data is handled. For example, the theory that we outlined in the introduction suggests that workers require greater compensation to attract them to sectors with higher turnover. This is a long-run relationship that is presumably unaffected by transitory movements in turnover. That is, a temporary increase in job destruction or worker separations in a sector that is traditionally characterized by low rates of turnover should not dissuade forward-looking workers from seeking employment in that sector. Likewise, a temporary reduction in turnover should not lull workers into falsely believing that employment in that sector is permanently more secure than previously believed. As such, we would expect to see even stronger correlations if we average turnover rates (by SIC) over the years of available data. Indeed, this is the case. Figures 5 and 6 show the scatter diagrams relating the value of the trade index to the average values of job destruction (Figure 5) and our proxy for job acquisitions (Figure 6). These averages, which vary by 2-digit SIC, are calculated from the DHS data and encompass the period 1973-1981. Figures 7 and 8, which portray the same relationships, are derived from BLS data on worker turnover. In these figures, the turnover data spans 1977-1981. The estimated slope coefficients (and their associated t-statistics) in Figures 5 and 7 are larger in

[23] The slope coefficient on the regression line in Figure 3 has a value of –2.936, corresponding to an elasticity of the absolute value of the trade index with respect to the separation rate well in excess of –3.0. This follows since the average of the absolute value of the trade index over this time span is 5.05, while the average separation rate is 4.05. The t-statistic corresponding to the slope coefficient is –7.48. and the adjusted R-squared is 0.357.

[24] The t-statistic on this coefficient is 1.21 and the adjusted R-squared is 0.005.

magnitude than their counterparts in Figures 1 and 3. There are no perceptible differences between the estimated slope coefficients in Figures 6 and 8 versus those in Figures 2 and 4.

We also explored the sensitivity of our results to the existence of outliers in the sample. Using the years for which DHS data is available, 257 of the 280 observations at the 2-digit level display values of $T_i \in [-13, 14]$. Moreover, the distribution of T_i over this interval is roughly symmetric. Similarly, using only the years for which BLS data is available, 95 out of 100 observations have values of $T_i \in [-12, 13]$. Again, within this range, the distribution of T_i is roughly symmetric. Re-running the simple bivariate regressions underlying Figures 1-8 does not yield substantively different results. Using these limited samples, our measure of the trade index continues to be negatively correlated with job destruction and worker separations (both contemporaneous and averaged over the years in the sample) and positively correlated with our proxy of job acquisitions (both contemporaneous and averaged over the years of the sample) when calculating this proxy based on the DHS data. As with the full sample, we cannot in the limited sample detect a statistically significant relationship between our trade index and the proxy for job acquisitions when we base our proxy on the BLS data.[25]

Using the full sample of data based on both 2-digit and 4-digit SIC categories, we regressed the trade index against both b and $\tilde{e}$ simultaneously for each year from 1973-1986 (using the DHS data) and 1977-1981 (using the BLS data). These results are reported in Tables 1-4. It is striking to observe that every estimated coefficient for b is negative, while all but one of the estimated coefficients for $\tilde{e}$ are positive.

In Tables 5-8, we add three control variables to see if after controlling for certain observable industry- and time-varying effects we can still observe a negative correlation between

[25] We are happy to provide these results to anyone requesting them.

the trade index and the job destruction or separation rate and a positive correlation between the trade index and the job acquisition rate. The first two variables that we control for are the (constant dollar) amount of capital per worker (k_{it}) and production workers as a share of total employment $(prodworker_{it})$.[26] The final control variable is a trade-weighted index of the value of the dollar $(dollar_t)$, with higher values meaning that the dollar is stronger.[27] This variable changes over time, but is common to all industries.

Also in Tables 5-8 we include the values of turnover by SIC averaged over time. An overbar indicates these values. For example, $\overline{b}_i$ in Table 5 is the average value of job destruction during the period 1973-1986 in the i^{th} SIC industry. We use the same symbol in Table 7 to refer to the average value of worker separations during the period 1977-1981 in the i^{th} SIC industry. Finally, we use the Greek letter delta to represent the percent deviation in year t of a variable from its sample mean. For example, Δb_{it} represents the percent deviation in job destruction (Tables 5 and 6) or worker separations (Tables 7 and 8) from the sample mean. If the theory outlined in the introduction of this paper is correct, we would expect the estimated coefficients on the long-run average values of turnover to be significant, with the coefficient on $\overline{b}_i$ estimated as negative, and that on $\overline{e}_i$ to be positive. On the other hand, if surging imports cause temporarily higher rates of job loss or worker separations, we would expect a negative sign on the coefficient of Δb_{it}. If export booms cause temporarily higher rates of job acquisition, we

[26] By including these variables, we are in no way attempting to test the factor endowment basis for trade. Indeed it has been well known at least since Leamer's (1984) work that such regressions are not an appropriate test of that model. Our only intent is to try to control for some obvious factors that might be correlated with the trade index to see if we can still observe any correlation with respect to job turnover rates.

[27] The data for these last two variables comes from the *Economic Report of the President*, various issues. The exchange rate index is the G-10 index.

would expect to see a positive sign on the estimated coefficient of $\Delta\overline{\widetilde{e}}_i$.[28] Thus, by including both the *average values* for turnover ($\overline{b}_i$ and $\overline{\widetilde{e}}_i$) and the deviations from the means (Δb_{it} and $\Delta\widetilde{e}_{it}$) we hope to gain insight as to the direction of causality.[29]

Tables 5-8 differ according to the degree of industry aggregation and the source of the turnover data. Tables 5 and 7 provide results derived from an analysis of 2-digit SIC data, while Tables 6 and 8 are based on 4-digit SIC data. Similarly, we used the job turnover data provided by DHS in deriving the results in Tables 5 and 6, while we used the BLS worker turnover data in generating Tables 7 and 8.

In every instance, the estimated coefficient of job destruction (or worker separations) is negative and highly significant. Similarly, the estimated coefficient of our job acquisition proxy, regardless of the source of the underlying data, is always positive and statistically significant.[30] These results provide strong support for they theory that the long-run pattern of turnover provides an independent basis of comparative advantage. By contrast, the estimated coefficients of the deviations between period t turnover and average turnover rates are small in magnitude, flip signs under alternative specifications, and are statistically no different than zero.[31] The failure to find any consistent relationship between trade balances and short-run movements in

[28] To further explore the possibility that temporary changes in an industry's trade balance cause temporary changes in turnover, we explicitly regressed the percent deviation in turnover (relative to the sample average) against the percent change in the trade index (relative to the sample average), treating the trade index as the exogenous variable. We conducted this analysis using both the DHS and BLS data at both the 2-digit and 4-digit levels. We were never able to reject the null hypothesis that the coefficient on the trade index was equal to zero.

[29] We discuss in the final section of this paper the problems inherent in using instrumental variables to sort through this issue.

[30] We also note that the "explanatory power" of turnover along (as measured by the value of $\overline{R}^2$) is always larger than the "explanatory power" of the three control variables. This is seen by comparing the final two columns of each of the tables. We should not make too much of the failure of *dollar* to yield the expected results in Tables 7 and 8 because there are only 5 years of data, and the index value of the dollar was exactly the same in 1977 as it was in 1981. It is quite understandable that we do not find an impact of this variable on trade since there is essentially no variation in this variable.

[31] Regarding the issue of magnitude, the estimated point elasticities implied by these coefficient estimates are uniformly less than 0.05.

turnover rates suggests that turnover is relatively insensitive to changes in exports or imports. We conclude that there is more evidence for our theory that turnover influences trade patterns than there is for the alternative hypothesis that changes in trade patterns influence turnover.

As a final check on the sensitivity of our results to outlying observations, we re-estimated the results in Tables 5 and 7 excluding the outliers.[32] In all cases, the estimated coefficients for b_{it} and $\overline{b}_{it}$ were negative. Moreover, they were highly statistically significant in all but one case. By contrast, the estimated coefficients for $\tilde{e}_{it}$ and $\overline{\tilde{e}}_{it}$ were positive in all but one case, but only statistically significant in the replication of regression (4).

4. Discussion.

Using two different sets of data that represent conceptually distinct measures of labor market turnover, we show the cross-industry pattern of net exports is strongly correlated with employment security. In particular, we showed that higher rates of job destruction or worker separations within an industry are consistently tied to lower levels of net exports from that industry. This correlation emerges whether we look at a cross-section of industries during a single year, or whether we pool all years together, and it emerges whether or not we control for other factors that we presume influence net exports. We also use the data on job creation and worker accessions to create a proxy for the job acquisition rate. We show that this proxy is positively correlated with net exports, but the correlation is not as strong as the link between job destruction or worker separations and net exports.

There are at least two problems with our results. The first is that we almost certainly face the problem of endogeneity. While it is a simple matter to write down a model where turnover is

[32] We did not re-estimate the regressions in Tables 6 and 8 because a review of the frequency distribution of the trade index calculated at the level of the 4-digit SIC industry revealed that there were no obvious outliers.

assumed exogenous, it would be hard to make a convincing argument that it is exogenous in the data. Of course, the standard procedure to correct for this problem is to instrument for turnover. However, this presents us with a fairly serious problem. Namely, all known correlates of job turnover (such as firm size, skill mix of the workforce, capital intensity of the industry, and so on) are surely correlated with the pattern of trade. As such, we are left with no choice but to recognize the problem but leave the empirical work where it stands.

The second problem is that, in some sense, our results are too strong. The theory sketched in the introduction is based on a *cross-country* comparison of intersectoral differences in turnover. Our data only applies to the United States. A more persuasive test of the theory would require the compilation of a data set including sector-specific turnover rates and trade variables for a variety of countries. If, for example, sector-specific turnover rates in the rest of the world exactly mirrored those in the United States, there would be no independent influence of turnover on the pattern of trade.[33] Conceptually, however, there are circumstances under which the ranking of sectors within the U.S. according to, say, the rate of job destruction is perfectly correlated with the ranking of sectors according to the rate of job destruction within the U.S. relative to that in the rest of the world. For example, if the rank-ordering of sectors by the rate of job destruction was the same in the U.S. as it is in the rest of the world, but if the variation across sectors is higher in the U.S. than elsewhere, then sectors with high rates of job destruction would also be those sectors where job destruction is high in the U.S. relative to elsewhere, and sectors with low rates of job destruction would also be those sectors where job destruction is low in the U.S. relative to elsewhere. It is plausible to argue that the variation across sectors in the rates of job destruction is indeed higher in the U.S., where labor markets are subject to relatively

[33] This is analogous to a a Heckscher-Ohlin model where two countries have the same factor endowments and the same production technologies. There would be no comparative advantage and no trade in this world.

little regulation, than in other countries where regulation is more heavy-handed. In the end, this is an empirical question.[34]

Fortunately, we can start to address this issue head on. In their cross-country comparison of job turnover, Baldwin, Dunne, and Haltiwanger (1998) report average job creation and job destruction rates over the period 1994-1992 for nineteen 2-digit SIC industries in the United States and Canada.[35] We can combine this data with data on bilateral trade between the United States and Canada to more closely approximate a true test of the underlying theory. Roughly speaking, the theory suggests that U.S. exports to Canada should be highest in industries where U.S. job destruction rates are lowest relative to Canadian job destruction rates.[36] More specifically, we define the index

$$(8) \qquad TC_{it} = \frac{EC_{it} - MC_{it}}{X_{it} + M_{it}} \times 100$$

where for industry i in year t EC_{it} represents U.S. exports to Canada and MC_{it} represents U.S. imports from Canada. This is simply net exports to Canada normalized by the total amount of trade (between the United States and all countries) associated with industry i in year t. The theory suggests that this index should be negatively correlated with the ratio of the industry-specific averages of U.S. job destruction relative to Canadian job destruction rates.

---

[34] Another problem is that the pattern of comparative advantage can actually be reversed if cross-country differences in average job acquisition rates are large enough. As an extreme example, suppose that the rate of job acquisition is infinite. In this case, cross-sector differences in job breakup rates are meaningless, since new jobs are found instantly upon losing an existing job. There is no role for a compensating wage differential. There will be a single wage in the economy. By contrast, wages will still be correlated with job destruction rates in a trading partner if the job acquisition rate in that country is finite. The country with the infinite rate of job creation will have a comparative advantage in the high-turnover sectors (assuming that the pattern of turnover is the same across countries).

[35] The data is reported in their Table 2. The reason that there are only nineteen industries is that they combine industries 38 (instruments) and 39 (miscellaneous products). They note in a footnote that there are slight discrepancies in industry definitions across countries.

[36] Lacking appropriate data to weight values of job creation, it is not possible to construct a proxy for job acquisition and therefore we cannot use a comparison of U.S. and Canadian job creation data in our analysis.

We regressed TC_{it} against the ratio of job destruction rates for nineteen 2-digit SIC industries for the years 1974-1994, providing a total of 399 observations. As is evident from Figure 9, there is indeed a negative relationship between (normalized) net exports from the U.S. to Canada and the ratio of job destruction rates. The estimated slope coefficient in this Figure is highly statistically significant, with a t-statistic of –13.10 and the regression line fits the data well as suggested by $\overline{R}^2 = 0.30$. While this result is certainly based on a very limited data set, we find it encouraging that it is consistent with our prior beliefs.

Taken in its entirety, we believe that the evidence presented in this paper provides sufficient grounds to encourage further research using alternative data and a sample of different countries to determine the pervasiveness and robustness of this empirical finding.[37]

[37] In a separate paper, written with Christopher Magee, we find empirical support for another result implied by the structural model presented in our 1999 paper. Namely, we show theoretically that the impact of trade on the welfare of factors of production that are employed in a particular sector depends on the rates of labor market turnover associated with that sector. At one extreme, with no turnover, the model behaves identically to a Ricardo-Viner specific-factors model. At the other extreme, with infinite turnover, the model behaves identically to a Heckscher-Ohlin model with Stolper-Samuelson effects. More generally, the impact of trade on worker welfare is a weighted average of the two effects, with the relative weight given to each determined by the degree of turnover. We find substantial support for this relationship using data on political contributions to Congress, Congressional voting patterns, and job destruction. See Magee, Davidson, and Matusz (2001).

References

Abowd, John, Patrick Corbel, and Francis Kramarz (1999), "The Entry and Exit of Workers and the Growth of Employment: An Analysis of French Establishments," *Review of Economics and Statistics*, 81: 170-187.

________ and Orley Ashenfelter (1981), "Anticipated Unemployment, Temporary Layoffs, and Compensating Wage Differentials," in *Studies in Labor Markets*, S. Rosen ed., University of Chicago Press, Chicago.

Albaek, Karsten and Bent Sorensen (1998), "Worker Flows and Job Flows in Danish Manufacturing, 1980-91," *Economic Journal*, 108: 1750-1771.

Acemoglu, Daron and Jorn-Steffen Pischke (1999), "Beyond Becker: Training in Imperfect Labour Markets," *Economic Journal*, 109: F112-42.

Baldwin, John, Timothy Dunn, and John Haltiwanger (1998), "A Comparison of Job Creation and Job Destruction in Canada and the United States," *The Review of Economics and Statistics*, 80: 347-356.

Baldwin, Robert and Christopher Magee (2000), *Congressional Trade Votes: From NAFTA Approval to Fast-Track Defeat*, Institute for International Economics, Washington, D.C.

Bartlesman, Eric J. and Wayne Gray (1996), "The NBER Manufacturing Productivity Database," NBER Technical Working Paper 205.

Bilsen, Valentijn and Jozef Konings (1998), "Job Creation, Job Destruction, and Growth of Newly Established, Privatized, and State-Owned Enterprises in Transition Economies: Survey Evidence from Bulgaria, Hungary, and Romania," in *Journal of Comparative Economics*, 26: 429-445.

Blanchard, Olivier and Augustin Landier (2001), "The Perverse Effects of Partial Labor Market Reform: Fixed Duration Contracts in France," NBER Working Paper 8219.

Blanchflower, David and Simon Burgess (1996), "Job Creation and Job Destruction in Great Britain in the 1980's," *Industrial and Labor Relations Review*, 50: 17-38.

Borland, Jeff (1996), "Job Creation and Job Destruction in Manufacturing Industry in Australia," *Economic Record*, 72: 46-62.

Chow, Clement, Michael Fung, and Ngo Hang Yue (1999), "Job Turnover in China: A Case Study of Shanghai's Manufacturing Enterprises," *Industrial Relations*, 38: 482-503.

Davidson, Carl, Lawrence Martin, and Steven Matusz (1999), "Trade and Search Generated Unemployment," *Journal of International Economics*, 48: 271-299.

Davis, Donald (1998), "Does European Unemployment Prop Up American Wages? National Labor Markets and Global Trade," *American Economic Review*, 88: 478-494.

Davis, Steven and John Haltiwanger (1992), "Gross Job Creation, Gross Job Destruction, and Employment Reallocation, *Quarterly Journal of Economics*, 107: 819-863.

__________ (1998), "Measuring Gross Worker and Job Flows," in *Labor Statistics Measurement Issues*, John Haltiwanger, Marilyn Manser and Robert Topel, eds., University of Chicago Press, Chicago.

Davis, Steven, John Haltiwanger, and Scott Schuh (1996), *Job Creation and Destruction*, The MIT Press, Cambridge, MA.

Feenstra, Robert C. (1996) , "U.S. Imports, 1972-1994: Data and Concordances," NBER Working Paper 5515.

__________ (1997), "U.S. Exports, 1972-1994, with State Exports and Other U.S. Data," NBER Working Paper 5990.

Freeman, Richard (1994), "How Labor Fares in Advanced Economies," in *Working Under Different Rules* (R. Freeman ed.), Russell Sage Foundation, New York.

Genda, Yuji (1998), "Job Creation and Destruction in Japan, 1991-1995," *Journal of the Japanese and International Economies*, 12: 1-23.

Krugman, Paul (1994), "Europe Jobless, America Penniless?" *Foreign Policy*, 95(Summer): 19-34.

Layard, Richard, Stephen Nickell, and Richard Jackman (1991), *Unemployment: Macroeconomic Performance and the Labour Market*, Oxford University Press, Oxford.

Ljungqvist, Lars and Thomas Sargent (1998), "The European Unemployment Dilema," *Journal of Political Economy*, 106: 514-550.

Magee, Christopher, Carl Davidson, and Steven Matusz (2001), "Trade, Turnover, and Tithing," manuscript.

Table 1

(Dependent Variable = T, results based on 2-digit SIC)

Year	Independent Variables (DHS Turnover Data) $\tilde{e}_{it}$	b_{it}	$\overline{R}^2$
1973	0.376 (1.29)	-1.611 (-3.17)	0.383
1974	0.824 (2.32)	-0.687 (-1.63)	0.232
1975	0.890 (2.64)	-0.161 (-0.685)	0.232
1976	0.450 (0.800)	-0.120 (-0.149)	-0.074
1977	0.780 (2.08)	-1.43 (-2.74)	0.326
1978	0.655 (1.54)	-1.202 (-1.70)	0.153
1979	0.310 (0.87)	-1.631 (-3.35)	0.393
1980	0.518 (1.33)	-1.062 (-1.91)	0.195
1981	0.970 (2.17)	-1.003 (-2.15)	0.232
1982	0.758 (1.57)	-.920 (-1.94)	0.184
1983	0.643 (1.11)	-5.85 (-1.29)	0.029
1984	0.093 (0.17)	-2.617 (-3.21)	0.325
1985	-0.026 (-0.07)	-2.114 (-6.15)	0.667
1986	0.650 (1.00)	-2.686 (-3.69)	0.411
1973-86	0.645 (4.96)	-0.652 (-6.27)	0.187

Notes: Estimated coefficients are listed in the body of the table, with t-statistics in parentheses. There are 20 observations in each year.

Table 2
(Dependent Variable = T, results based on 4-digit SIC)

Year	Independent Variables (DHS Turnover Data) $\tilde{e}_{it}$	b_{it}	$\bar{R}^2$
1973	2.388	-0.441	0.029
	(1.36)	(-3.48)	
1974	4.433	-0.400	0.047
	(2.23)	(-4.09)	
1975	3.056	-0.258	0.042
	(1.73)	(-4.05)	
1976	0.165	-0.005	-0.004
	(0.10)	(-0.04)	
1977	2.554	-0.366	0.030
	(1.32)	(-3.72)	
1978	4.420	-0.786	0.089
	(2.27)	(-6.42)	
1979	3.012	-0.829	0.085
	(1.68)	(-6.16)	
1980	3.127	-0.412	0.039
	(1.68)	(-3.95)	
1981	3.250	-0.358	0.027
	(1.75)	(-3.26)	
1982	2.954	-0.389	0.072
	(1.73)	(-5.63)	
1983	2.066	-0.138	0.008
	(1.24)	(-1.89)	
1984	1.884	-0.550	0.044
	(0.975)	(-4.55)	
1985	3.240	-0.796	0.139
	(1.90)	(-8.162)	
1986	3.957	-0.716	0.084
	(2.017)	(-6.076)	
1973-86	2.941	-0.360	0.042
	(5.93)	(-15.13)	

Notes: Estimated coefficients are listed in the body of the table, with t-statistics in parentheses. There are 20 observations in each year.

Table 3

(Dependent Variable = T, results based on 2-digit SIC)

Year	Independent Variables (BLS Turnover Data) $\tilde{e}_{it}$	b_{it}	$\bar{R}^2$
1977	0.774	-3.156	0.423
	(2.03)	(-3.93)	
1978	0.691	-2.98	0.388
	(1.64)	(-3.68)	
1979	0.706	-3.284	0.418
	(1.69)	(-3.88)	
1980	0.796	-3.987	0.509
	(1.99)	(-4.16)	
1981	0.795	-4.393	0.413
	(1.86)	(-3.84)	
1977-81	0.735	-3.408	0.451
	(4.21)	(-8.98)	

Notes: Estimated coefficients are listed in the body of the table, with *t*-statistics in parentheses. There are 20 observations in each year.

Table 4

(Dependent Variable = T, results based on 4-digit SIC)

	Independent Variables (BLS Turnover Data)		
Year	$\tilde{e}_{it}$	b_{it}	$\bar{R}^2$
1977	1.258 (1.00)	-2.641 (-5.24)	0.201
1978	1.809 (1.42)	-2.836 (-6.05)	0.263
1979	2.641 (2.08)	-3.053 (-6.29)	0.264
1980	2.180 (1.79)	-3.510 -(5.90)	0.238
1981	2.285 (1.72)	-3.236 (-4.95)	0.177
1977-81	2.029 (3.61)	-3.013 (-12.76)	0.233

Notes: Estimated coefficients are listed in the body of the table, with *t*-statistics in parentheses. There are 106 observations in each year.

Table 5

(Dependent Variable = T, results based on 2-Digit SIC, DHS turnover data)

Independent Variables	(1)	(2)	(3)	(4)	(5)
b_{it}	-0.424 (-4.06)				
$\overline{b}_i$		-2.457 (-10.60)	-2.458 (-10.56)	-2.241 (-12.89)	
Δb_{it}			0.005 (0.47)		
$\tilde{e}_{it}$	0.389 (2.75)				
$\overline{\tilde{e}}_{it}$		0.762 (5.73)	0.764 (5.74)	0.837 (7.35)	
$\Delta\tilde{e}_{it}$			0.020 (1.10)		
k_{it}	-0.002 (-0.34)	-0.012 (-2.24)	-0.012 (-2.22)		-0.006 (-1.16)
$prodworker_{it}$	-0.330 (-5.98)	0.142 (0.238)	0.015 (0.25)		-0.440 (-8.64)
$dollar_t$	-0.111 (-4.06)	-0.108 (-4.70)	0.111 (-4.64)		-0.141 (-5.14)
$\overline{R}^2$	0.315	0.474	0.473	0.421	0.245
N	280	280	280	280	280

Note: Estimated coefficients are in the body of the table, with t-statistics in parentheses.

Table 6

(Dependent Variable = T, results based on 4-Digit SIC, DHS turnover data)

Independent Variables	(1)	(2)	(3)	(4)	(5)
b_{it}	-0.267 (-11.55)				
$\overline{b}_i$		-1.147 (-23.11)	-1.144 (-23.04)	-1.393 (-29.9)	
Δb_{it}			-0.001 (-0.27)		
$\tilde{e}_{it}$	1.853 (3.84)				
$\overline{\tilde{e}}_{it}$		2.492 (4.93)	2.496 (4.94)	3.803 (7.47)	
$\Delta\tilde{e}_{it}$			0.006 (1.72)		
k_{it}	0.000 (3.49)	0.000 (-1.23)	0.000 (-1.10)		0.000
$prodworker_{it}$	-0.355 (-22.44)	-0.256 (-15.89)	-0.257 (-15.93)		-0.384 (-24.39)
$dollar_t$	-0.117 (-11.14)	-0.123 (-12.20)	-0.121 (-11.92)		-0.135 (-12.85)
$\overline{R}^2$	0.129	0.180	0.182	0.132	.108
N	6258	6258	6258	6258	6258

Note: Estimated coefficients are in the body of the table, with t-statistics in parentheses.

Table 7

(Dependent Variable = T, results based on 2-Digit SIC, BLS turnover data)

Independent Variables	(1)	(2)	(3)	(4)	(5)
b_{it}	-3.737 (-6.82)				
$\overline{b}_i$		-4.100 (-7.32)	-4.103 (-7.25)	-3.580 (-9.44)	
Δb_{it}			0.017 (0.18)		
$\tilde{e}_{it}$	0.565 (3.04)				
$\overline{\tilde{e}}_{it}$		0.599 (3.28)	0.600 (3.24)	0.757 (4.42)	
$\Delta\tilde{e}_{it}$			-0.002 (-0.02)		
k_{it}	-0.023 (-2.96)	-0.025 (-3.24)	-0.025 (-3.21)		-0.10 (-1.15)
$prodworker_{it}$	-0.047 (-0.57)	-0.009 (-0.11)	-0.009 (-0.10)		-0.439 (-5.97)
$dollar_t$	-0.086 (-1.16)	-0.014 (-0.19)	-0.007 (-0.08)		-0.017 (-0.19)
$\overline{R}^2$	0.489	0.517	0.504	0.476	0.248
N	100	100	100	100	100

Note: Estimated coefficients are in the body of the table, with t-statistics in parentheses.

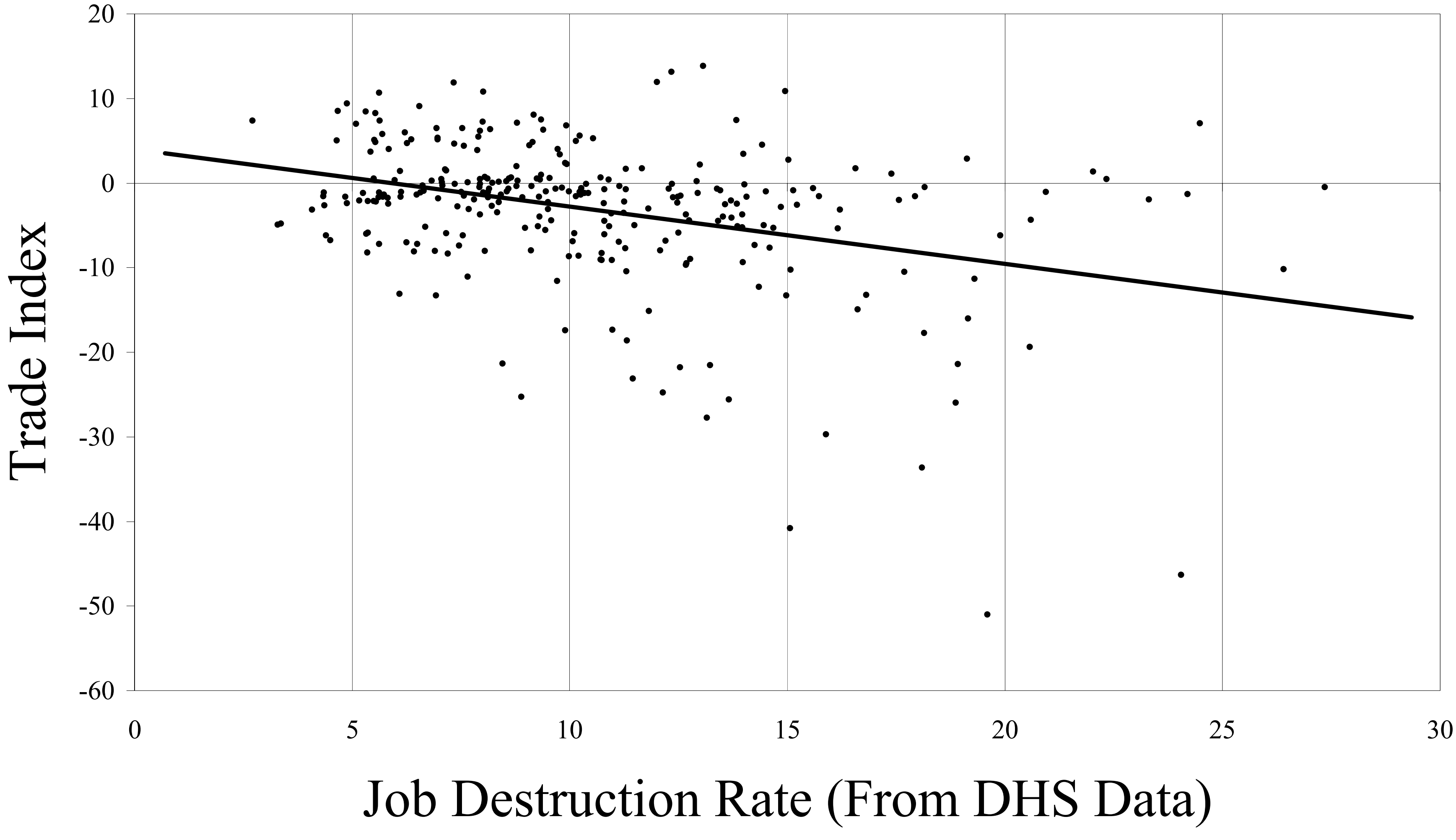
Table 8

(Dependent Variable = T, results based on 4-Digit SIC, BLS turnover data)

Independent Variables	(1)	(2)	(3)	(4)	(5)
b_{it}	-2.205 (-7.74)				
$\bar{b}_i$		-2.571 (-8.36)	-2.572 (-8.34)	-3.314 (-13.56)	
Δb_{it}			-0.004 (-0.12)		
$\tilde{e}_{it}$	1.690 (3.06)				
$\bar{\tilde{e}}_{it}$		1.905 (3.41)	1.906 (3.40)	2.218 (3.94)	
$\Delta\tilde{e}_{it}$			-0.013 (-0.37)		
k_{it}	0.000 (-0.78)	0.000 (-1.25)	0.000 (-1.25)		0.000 (1.12)
$prodworker_{it}$	-0.247 (-5.68)	-0.216 (-4.86)	-0.215 (-4.84)		-0.429 (-11.16)
$dollar_t$	-0.022 (-0.38)	0.013 (0.22)	0.011 (0.19)		0.008 (0.13)
$\bar{R}^2$	0.275	0.287	0.285	0.256	0.195
N	530	530	530	530	530

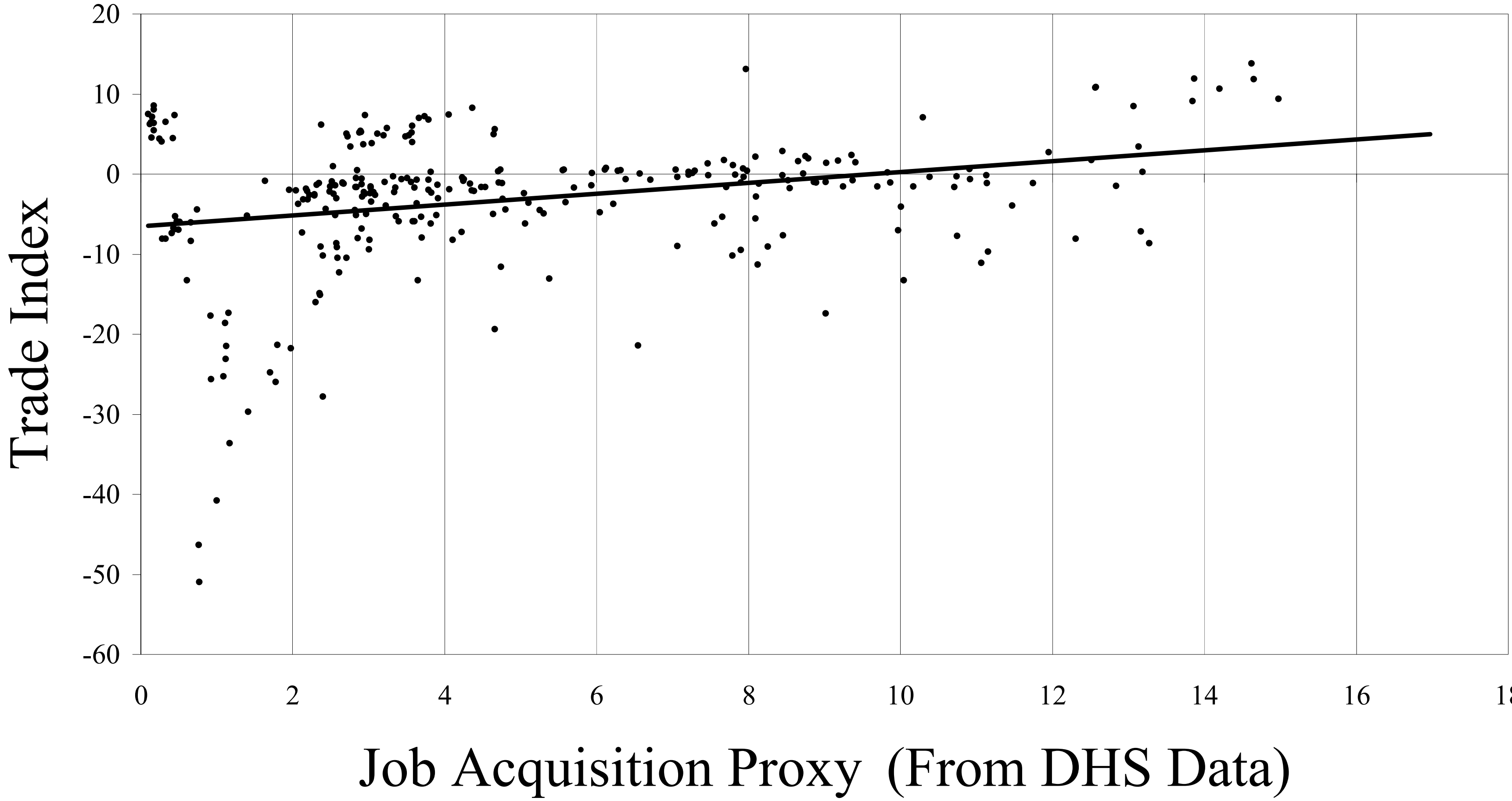
Note: Estimated coefficients are in the body of the table, with t-statistics in parentheses.

Figure 1



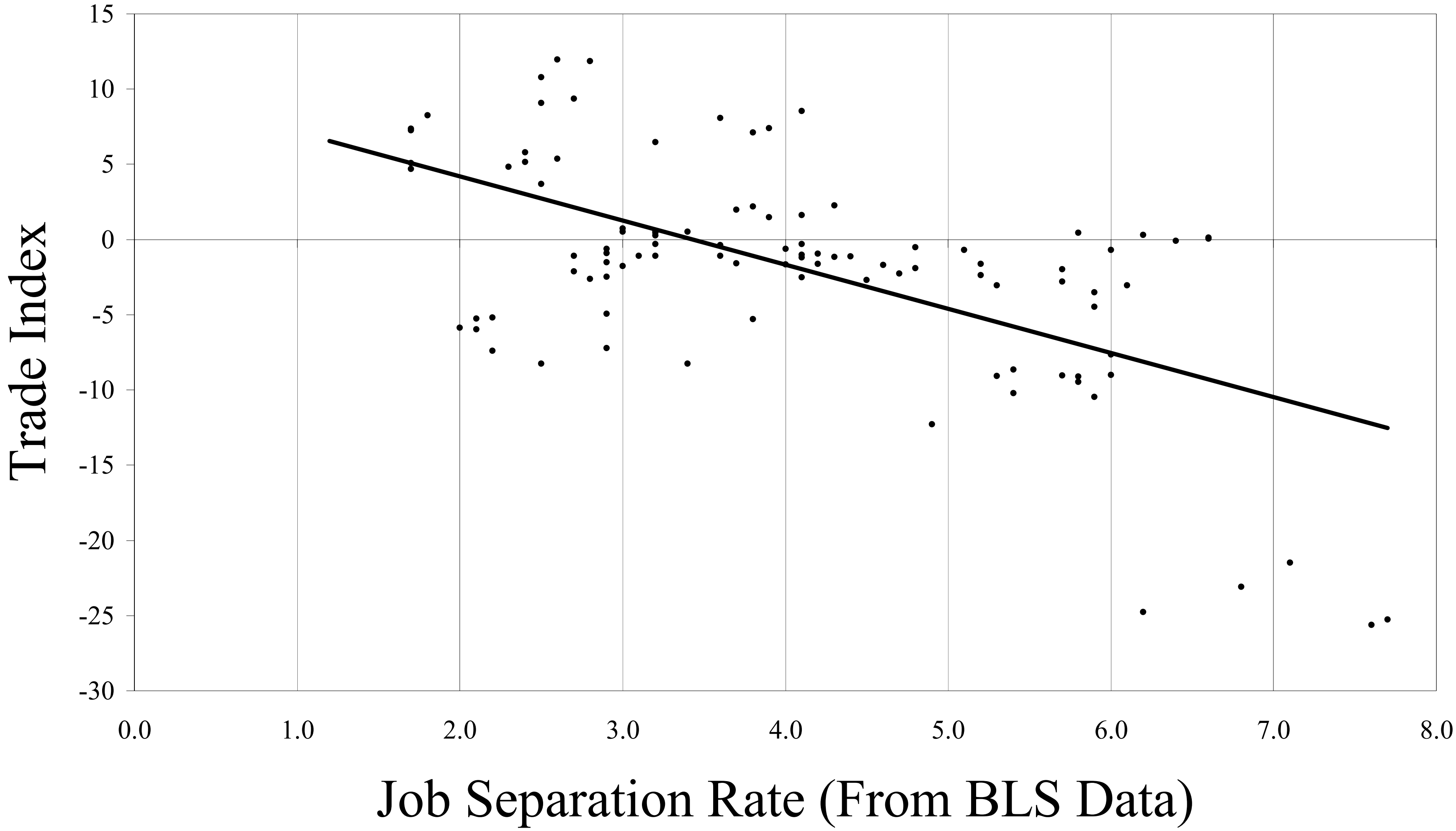
20
10
0
-10
-20
-30
-40
-50
-60
Trade Index
0
5
10
15
20
25
30
Job Destruction Rate (From DHS Data)

Figure 2



20
10
0
-10
-20
-30
-40
-50
-60
0
2
4
6
8
10
12
14
16
18
Trade Index
Job Acquisition Proxy (From DHS Data)

Figure 3



15
10
5
0
-5
-10
-15
-20
-25
-30
Trade Index
0.0
1.0
2.0
3.0
4.0
5.0
6.0
7.0
8.0
Job Separation Rate (From BLS Data)

Figure 4

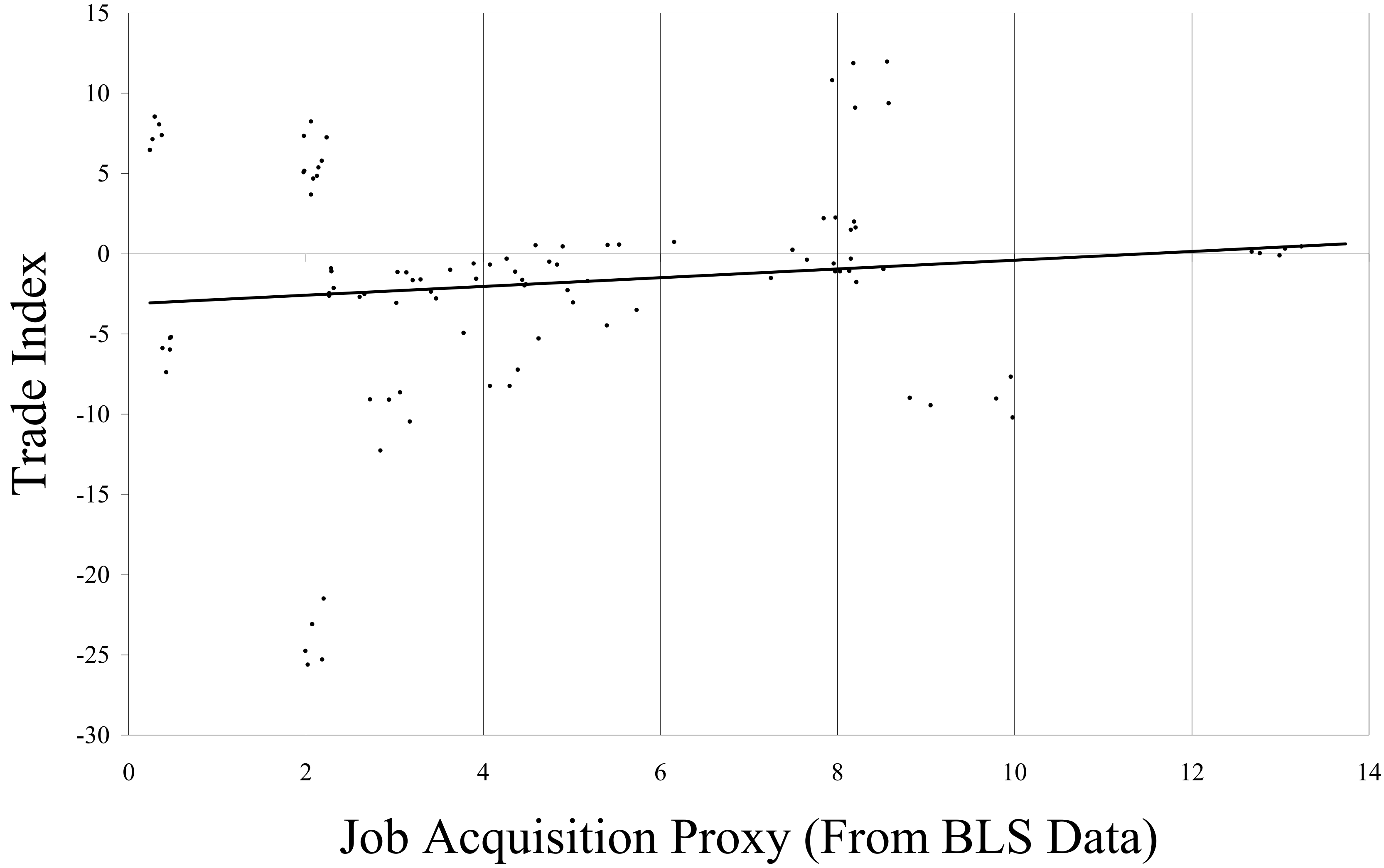
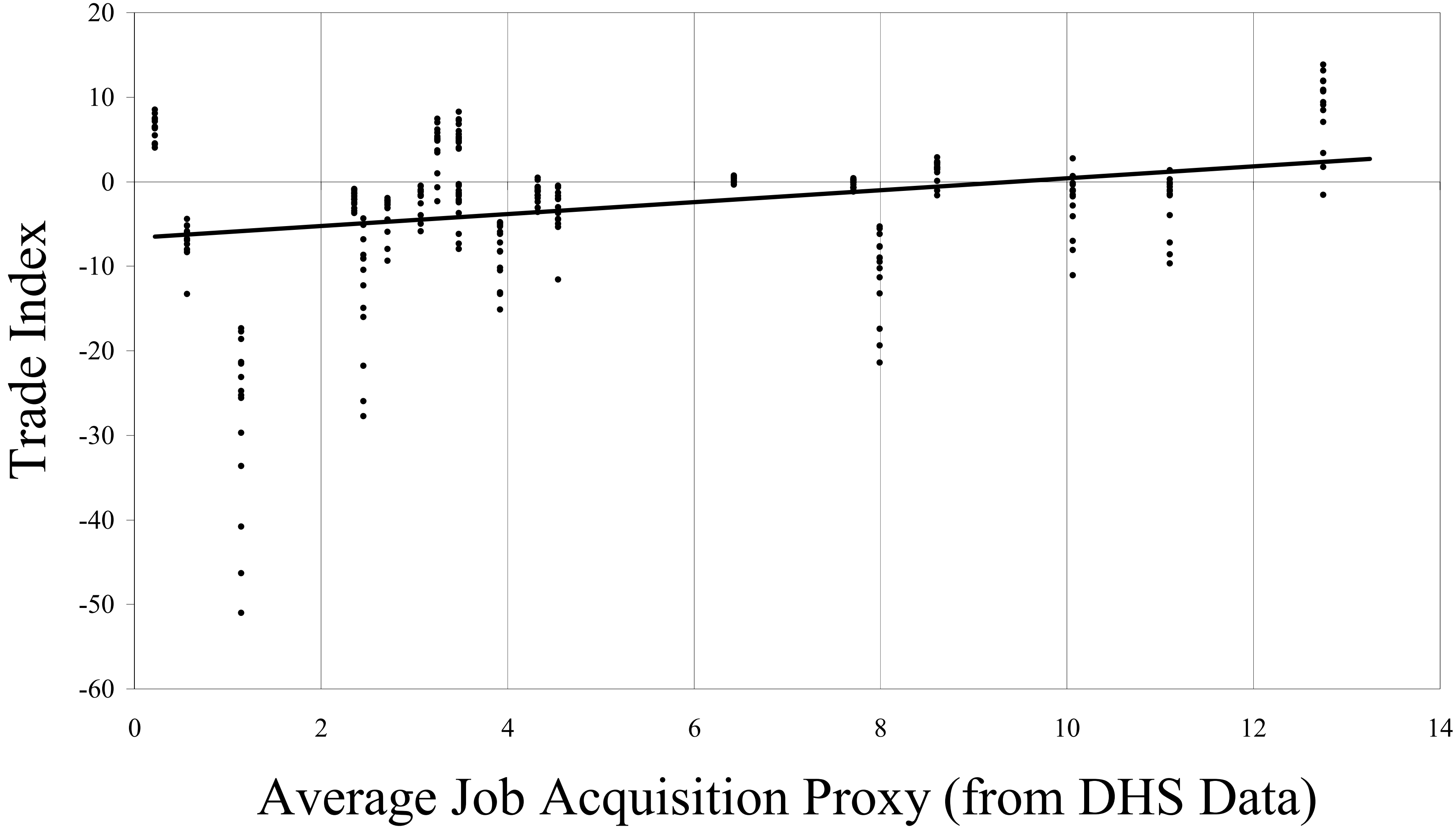

Trade Index
15
10
5
0
-5
-10
-15
-20
-25
-30
0
2
4
6
8
10
12
14
Job Acquisition Proxy (From BLS Data)

Figure 5

20
10
0
-10
-20
-30
-40
-50
-60
Trade Index
6
7
8
9
10
11
12
13
14
15
16
Average Job Destruction Rate (From DHS Data)

Figure 6

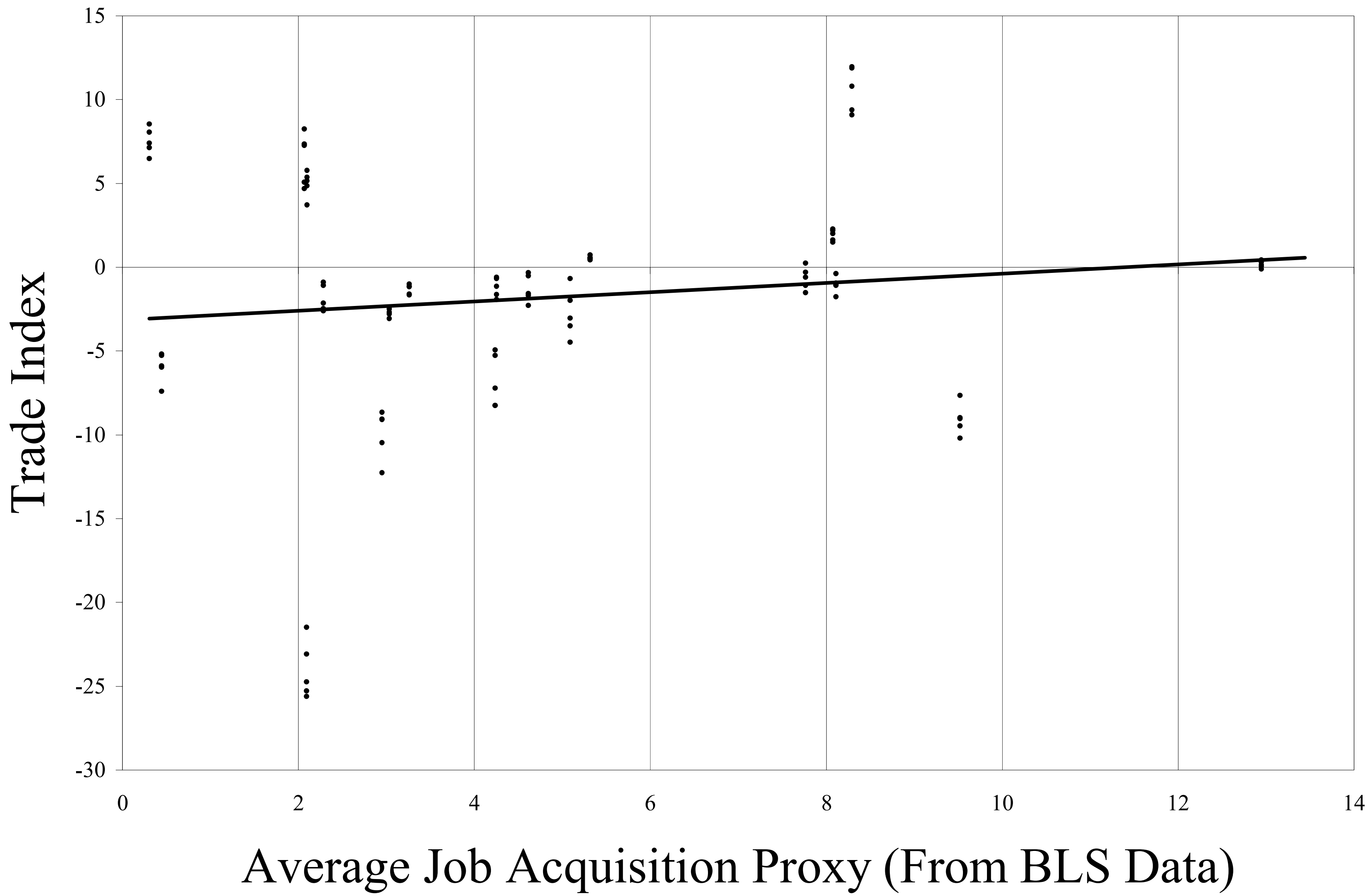


20
10
0
-10
-20
-30
-40
-50
-60
Trade Index
0
2
4
6
8
10
12
14
Average Job Acquisition Proxy (from DHS Data)

Figure 7

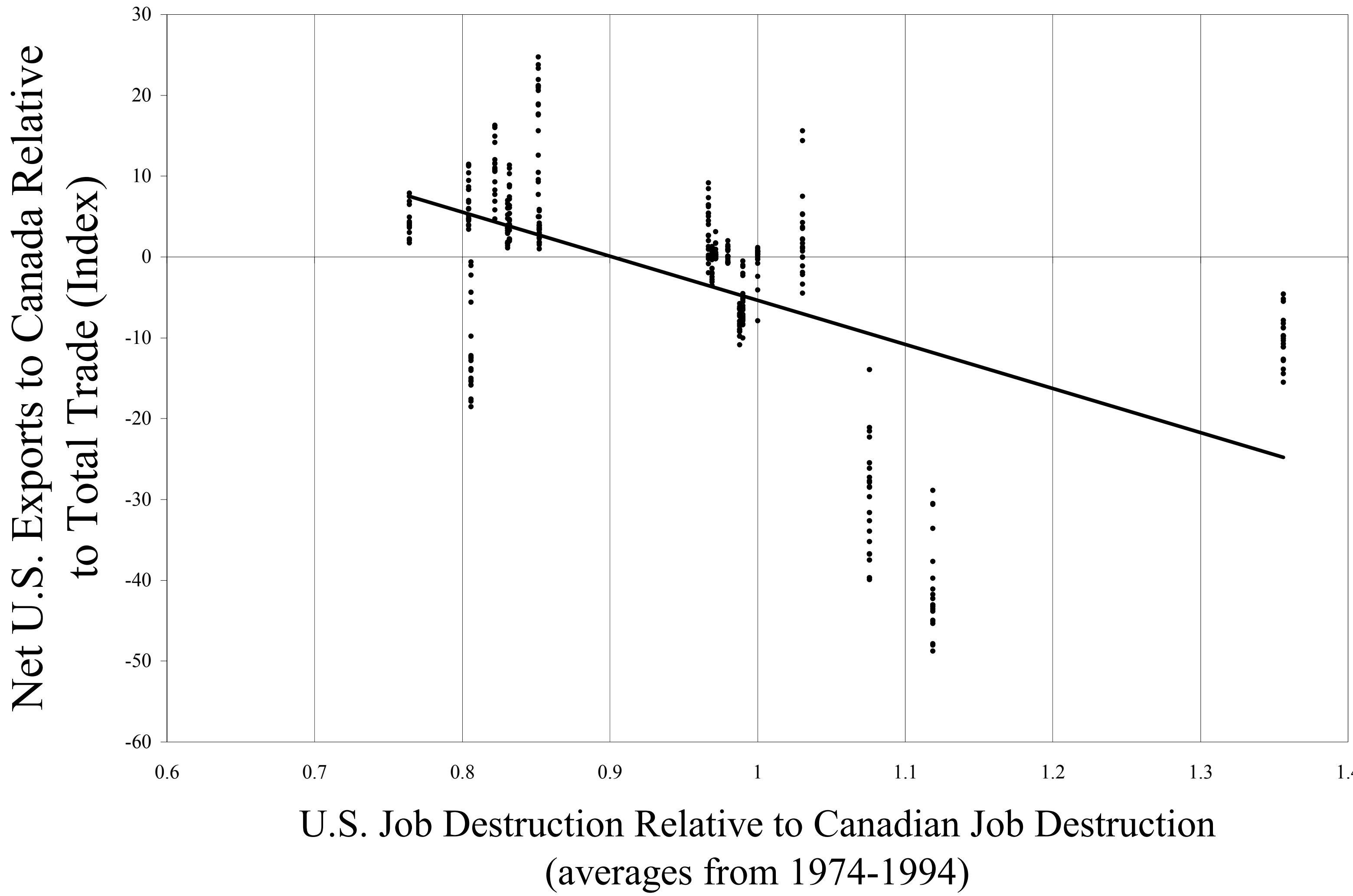

15
10
5
0
-5
-10
-15
-20
-25
-30
Trade Index
0.0
1.0
2.0
3.0
4.0
5.0
6.0
7.0
8.0
Average Job Separation Rate (From BLS Data)

Figure 8



Trade Index
15
10
5
0
-5
-10
-15
-20
-25
-30
0
2
4
6
8
10
12
14
Average Job Acquisition Proxy (From BLS Data)

Figure 9



Net U.S. Exports to Canada Relative to Total Trade (Index)
30
20
10
0
-10
-20
-30
-40
-50
-60
0.6
0.7
0.8
0.9
1
1.1
1.2
1.3
1.4
U.S. Job Destruction Relative to Canadian Job Destruction
(averages from 1974-1994)