Preliminary and Incomplete

Trade and Turnover: Theory and Evidence

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1. Introduction.

2. The Model.

To fix ideas, we consider an economy capable of producing two goods (X_1 and X_2) using labor as the only input. We assume that workers are heterogeneous in their abilities, but each employed worker is paid the value of his marginal product. In particular, we index worker ability by $a \sim [0,1]$, and assume that a worker with ability *a* can produce $q_i(a)$ units of X_i where

(1) $$q_i(a) = a^{h_i}.$$

We further assume that $h_1 < 1 < h_2$. This implies that at low levels of ability, a small increase in ability has a relatively big payoff in terms of productivity in sector 1, but the marginal benefit of increased ability becomes smaller as ability levels increase. The situation is reversed in sector 2, where the marginal product of labor increases at an increasing rate as ability increases.

If this lifetime employment was guaranteed in both sectors, then workers would sort themselves into sectors according to their abilities. Define the marginal worker as one who is just indifferent between sectors. Let a_H be the ability level of this worker. Defining X_1 as the numeraire good and letting the p represent the price of X_2, a_H would be the solution to $q_1(a_H) = pq_2(a_H)$. It is easily verified by substitution from (1) that workers with ability levels lower than a_H would earn strictly higher wages in sector 1 while workers with higher ability would earn strictly higher wages in sector 2. Therefore, all workers in sector 2 would have higher abilities than any (but perhaps the marginal) worker in sector 1.

The focus of our paper, however, is on how labor turnover exerts an independent influence on the sectoral pattern of employment and, consequently, on the pattern of comparative advantage between countries. As such, we abandon the assumption of lifetime employment and opt instead for a model where workers cycle back and forth between employment and unemployment.[1] In particular, we assume in the context of a continuous-time framework that jobs in sector *i* are lost at a flow rate of b_i and that those searching for employment in sector *i* acquire jobs at a flow rate of e_i.[2] Let $L_{iE}(t)$ and $L_{iS}(t)$ represent the mass of workers employed and searching for employment in sector *i* at time *t*, and let $L_i(t) = L_{iE}(t) + L_{iS}(t)$. Using a dot over top of a variable to denote the time-derivative of that variable, the differential equations corresponding to this circular flow of workers between employment and unemployment are

$$(2) \qquad \dot{L}_i(t) = \dot{L}_{iE}(t) + \dot{L}_{iS}(t)$$

$$(3) \qquad \dot{L}_{iE}(t) = e_i L_{iS}(t) - b_i L_{iE}(t).$$

The steady-state solution to this system is then

$$(4) \qquad L_{iE} = \frac{e_i}{e_i + b_i} L_i.$$

We can solve for the mass of workers in each sector by solving for L_i. But solving for L_i merely requires solving for the ability level of the marginal worker. As we will presently show, there is a perfect analogy with the lifetime employment model in that once we find this critical level of ability; all workers with lower ability will sort themselves into sector 1, while all workers with higher ability will sort themselves into sector 2.

Before proceeding, we note that employed workers in either sector could always quit and search for a job in the other sector. But this would not be rational behavior in a steady state.

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[1] There is strong substantial empirical evidence that job creation and job destruction is substantial and pervasive, both in the United States and in other countries. In particular, there is substantial job loss (measured at the establishment level) even in sectors that are increasing in net size, and substantial job creation even in sectors that are declining in size. See, for example, Davis, Haltiwanger, and Schuh (1996), Bilsen and Konings (1998), Baldwin, Dunne, and Haltiwanger (1998), and Haltiwanger and Vodopivec (2000).

Presumably, each worker begins as a searcher and chooses the sector in which to search based upon expected lifetime income. In an equilibrium with diversified production, the expected lifetime income from searching must be the same in both sectors. Since the expected lifetime income from someone who is currently employed in sector *i* is higher than that of a worker searching for a job in sector *i*, it follows that a worker currently employed in sector *i* enjoys higher expected lifetime income than he would if he were to search for a job in sector *j*.

Let $V_{iE}(a)$ and $V_{iS}(a)$ be the expected lifetime income earned by a worker who is employed or searching for a job in sector *i*. If we assume that the worker earns no income while searching, we can show that[3]

$$(5) \qquad rV_{iE}(a) = \frac{r + e_i}{r + b_i + e_i} w_i(a)$$

$$(6) \qquad rV_{iS}(a) = \frac{e_i}{r + b_i + e_i} w_i(a)$$

where r is the discount rate and $w_i(a)$ is the sector-*i* wage for a worker with ability a.[4] Equations (5) and (6) have natural interpretations. The expected lifetime income of a worker under any given circumstance equals a weighted average of what the worker earns while employed (w_i) and while unemployed (0). The weights are the fraction of the worker's life during which he is either employed or unemployed, adjusted to provide a bit more weight on the current activity. That is, the weight on the wage for a currently employed worker is a bit higher than it is for an unemployed worker.

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[2] We are assuming Poisson processes here. As such, the expected duration of a job is the inverse of b_i, while the expected duration of a spell of unemployment is the inverse of e_i.

[3] We provide the complete derivation of (5) and (6) in the Appendix.

[4] The lifetime employment model can be seen as a special case by simply letting both e_1 and e_2 tend to infinity.

Remembering that each worker is paid the value of his marginal product, we can use (1) and (6) to solve for the ability level of the marginal worker:

$$(7) \qquad a_H = \left[\frac{e_1}{e_2} \frac{r+b_2+e_2}{r+b_1+e_1} \frac{1}{p} \right]^{\frac{1}{h_2-h_1}} .$$

The solution to (7) is illustrated in Figure 1. Equation (7) forms the basis of our first result.

Proposition 1: Given the assumption that $h_2 > h_1$, the ability level of the marginal worker is increasing in b_1 and e_2, while it is decreasing in b_2, e_1, and p.

The proof of Proposition 1 follows directly from inspection of (7). Moreover, a brief glance at Figure 1 makes it plain that this result does not depend in any critical way on the particular functional form assumed in (1). All that is required is that the increase in expected lifetime income due to increased ability is increasing more rapidly in one sector than in the other.[5] The intuition of this result is simple. Increasing p raises the wage rate in sector 2 regardless of the level of ability. The curve in Figure 1 that is labeled $V_{2S}(a)$ rotates upward and a_H falls. Likewise, decreasing b_2 means that jobs in sector 2 last longer, while increasing e_2 means that such jobs are easier to find. Parallel results follow for changes in b_1 and e_1.

Finally, we can use (1), (4) and (7) to solve for the steady state quantity of output produced in each sector:

$$(8.a) \qquad Q_1 = \frac{e_1}{b_1+e_1} \int_0^{a_H} f(a) a^{h_1} da$$

$$(8.b) \qquad Q_2 = \frac{e_2}{b_2+e_2} \int_{a_H}^{1} f(a) a^{h_2} da$$

[5] We need some slight restrictions on functional form to generate a unique solution for a_H, but a wide variety of functional forms will satisfy these conditions.

where $f(a)$ represents the density function of ability. Our next result follows from equations (8.a) and (8.b), combined with Proposition 1.

Proposition 2: The steady state value of $_{i}$ p_i, e_i and b_j, while it is decreasing in p_j, e_j and b_i, where $i \neq j$.

Proof: The proof of Proposition 2 is in two parts. First, from Proposition 1, an increase in p_i or e_i or a decrease in b_i will result in a lower ability level of the marginal worker. In other words, the range of workers who choose to look for employment in sector *i* will expand and fewer will choose to search in the other sector. Second, if the turnover rates change, an increased proportion of those who are attached to sector *i* will find themselves employed in the steady state. Both effects work to increase the steady state value of Q_i. The first effect works to decrease the steady state value of Q_j.

If we assume homothetic preferences, thereby neutralizing any possible complications arising from income effects, we arrive at the following corollary.

Corollary 1: Autarkic equilibrium exists and is unique.

The proof of this result follows from the fact that Q_2/Q_1 is strictly increasing in *p*. Furthermore, there exists a low enough value of *p* such that this ratio is zero and a high enough value such that this ratio approaches infinity. At the same time, the ratio of good 2 demanded to good 1 demanded is strictly decreasing in *p*. The autarkic equilibrium is illustrated in Figure 2.

To conclude this section, we now add a second country to explore how cross-country differences in the sectoral pattern of job turnover can exert an independent influence on the pattern of comparative advantage.[6] To neutralize factors such as factor supplies or technological differences as a source of comparative advantage, we assume that the second country is identical to the first in terms of preferences, production technology, and the distribution of ability across workers. We also assume that the values of e_1 and b_1 are the same in both countries.[7]

Proposition 3: (a) If $e_2 = e_2^*$, the home country has a comparative advantage in the production of good 2 if and only if $b_2 < b_2^*$, where the asterisk is used to designate the value of the variable in the foreign country. (b) If $b_2 = b_2^*$, the home country has a comparative advantage in the production of good 2 if and only if $e_2 > e_2^*$

Proof: To prove this result, note from Proposition 2 that a either a decrease in b_2 or an increase in e_2 will lead to a steady state increase in Q_2 and a steady state decrease in Q_1. This result is independent of price (as long as both goods are being produced prior to the parametric change). In terms of Figure 2, the relative supply curve shifts to the right, decreasing the equilibrium value of *p*.

This result is fairly intuitive. All else equal, workers are attracted to jobs that have relatively greater security and jobs that relatively easy to obtain. All else equal, the endogenously determined allocation of labor across sectors will systematically differ across countries to the extent that these patterns of durability and ease of attainment differ across countries.

[6] There are substantial differences in job turnover between countries. For example, as reported by Davis, Haltiwanger, and Schuh (1996) in their Table 2.2, the average job destruction rate in Germany was 7.7 percent, while it was almost 20 percent in New Zealand (albeit that the time frames do not match). Similarly, the job creation rate was 7.1 percent in Norway and a whopping 18.6 percent in Morocco. Of course, differences in overall average rates of job creation and job destruction need not imply differences in the sectoral patterns across countries. Indeed, Baldwin, Dunne, and Haltiwanger (1998) find that industries with high rates of job destruction in the United States also have high rates of job destruction in Canada. Similar results obtain for job creation. However, there is little evidence comparing economies with substantially different institutions.

3. The Data.

As noted in the introduction, Davis, Haltiwanger, and Schuh used the Longitudinal Research Database (LRD) developed by the United States Census Bureau to create a statistical portrait of job creation and job destruction in the United States between 1972 and 1988. The purpose of this section is to describe that data and to discuss the conceptual fit between the DHS data and the theoretical model outlined in Section 2.[8]

The LRD combined data from the quinquennial census of manufactures with annual survey data to ascertain, inter alia, establishment-level employment numbers.[9] 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.[10]

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 up 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 establishments in this group is denoted by S^-. Of course the remaining establishments (presumably accounting for only a very

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[7] Allowing these other parameters to vary generates straightforward results. Holding e_1 and b_1 constant across countries is a mere simplification.
[8] Of course the authoritative (and complete) description of the dataset is provided by Davis, Haltiwanger, and Schuh (1996).
[9] In this context, an establishment is a plant employing (generally speaking) five or more workers.
[10] Establishments rotated in and out of the sample at 5-year intervals.

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

$$C_{st} = \sum_{e \in S^+} \left(N_{et} - N_{e,t-1} \right) \tag{9}$$

$$c_{st} = \frac{C_{st}}{\frac{1}{2} \sum_{e \in S} \left(N_{et} + N_{e,t-1} \right)} \tag{10}$$

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 Section 2 of this paper. The problem is that it does not really tell us how easy or hard it is to find a job in a particular sector. 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. 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. Even so, it is possible to use this measure to tease out an expression that has some bearing on the issue at hand.

The relative supply of new jobs created by firms in sector *S* relative to manufacturing firms in all sectors provides some sense of the absolute 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 l_{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[11]

$$c_t = \sum_i l_{it} c_{it} \,. \tag{11}$$

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

$$\tilde{e}_{jt} = \frac{l_{jt} c_{jt}}{c_t} \,. \tag{12}$$

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 (12) is not a perfect proxy for the true job acquisition rate, since we know nothing about the pool of workers suited to 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.

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.[12] Then by definition

$$B_{st} = \sum_{e \in S^-} \left| N_{et} - N_{e,t-1} \right| \tag{11}$$

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

$$(12) \qquad b_{st} = \frac{B_{st}}{\frac{1}{2}\sum_{e\in S}\left(N_{et} + N_{e,t-1}\right)}.$$

The picture of job turnover as portrayed by Davis, Haltiwanger and Schuh (1996) is very much in the spirit of our theoretical model. Regardless of how the data is sliced, there appears to be substantial job turnover. In particular, job destruction is a prominent feature of the data even in growing sectors, and job creation is pervasive even in shrinking sectors. Davis, Haltiwanger and Schuh attribute this to firm heterogeneity even within narrowly defined sectors. While we do not formally model the source of this heterogeneity, we appealed to this empirical regularity in motivating the turnover inherent in our model. It is the fact that it is *involuntary* job loss that drives the model that makes the DHS measure of job destruction (as opposed to measures of worker mobility that might be derived from the CPS) relatively well suited for investigating the reasonableness of our model. This follows from the fact that measures of worker mobility confound both voluntary and involuntary reasons for job loss.[13]

In order to look for a correlation between job destruction and trade patterns, we combine the DHS dataset, provided at the 2-digit and 4-digit SIC levels, with data on U.S. trade that was compiled by Robert Feenstra and made available from the National Bureau of Economic Research.[14] 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.[15]

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[12] DHS use D_t to represent this variable.

[13] While there may be an element of voluntary job loss driving the job mobility numbers (e.g., some establishments may fail to replace retiring employees), the problem appears more acute with data on worker mobility. 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.

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

[15] 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).

3. Empirical Results.

Before turning to our own results, we would be remiss if we did not mention the fact that Davis, Haltiwanger and Schuh (1996) also inspected the data to see if there was a correlation between job destruction and trade. 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 rate 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 the 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."[16]

In order to explore more thoroughly the possible connection between job destruction 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

$$T_{it} = \frac{E_{it} - M_{it}}{Q_{it} + M_{it}} \times 100 \tag{13}$$

[16] See Davis, Haltiwanger, and Schuh (1996), p. 175).

where E_{it} and M_{it} represent gross exports and imports attributed to sector *i* during year *t*. This measure ranges between +100 (if there are no imports and if all output is exported) to –100 (if there is no domestic production and no re-export of imports).[17] The model in Section 2 of this paper loosely suggests that industries with higher job acquisition rates and lower job destruction rates should have a comparative advantage over industries with lower job acquisition rates and higher job destruction rates.[18] 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 Figure 3 and 4 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 nineteen 2-digit manufacturing industries per year, there are a total of 266 observations.[19] The slopes of the OLS regression lines in Figures 3 and 4 have the expected signs. Moreover, the slopes are both large in magnitude and highly statistically significant.[20]

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, using data based on both 2-digit and

[17] The qualitative nature of our results are substantially unaffected if instead we were to use import penetration as our dependent variable.

[18] This is only a loose interpretation of the model since Proposition 3 refers to differences in the patterns of job destruction rates *across countries*. Our data only applies to the United States, so we do not have a direct test of the model. We return to this issue in the conclusion of the paper.

[19] As we note later in this section, the DHS data pertaining to the 2-digit industries is disaggregated to account for job destruction by continuing establishments versus those that shut down. In this disaggregation, Davis, Haltiwanger and Schuh were forced to combine data for SIC 20 (food and kindred products) and SIC 21 (Tobacco Manufactures) to avoid disclosing the identities of individual establishments. We make use of this disaggregation in the later statistical analysis, so for continuity of our results we begin with the data that combines these two industries.

[20] The slope coefficient in Figure 3 has a value of –0.63 and an associated *t*-statistic of –5.7. The slope coefficient in Figure 4 has a magnitude of 0.95 and an associated *t*-statistic of 6.9. 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 5.3 (author's calculations). Evaluated at the sample mean, the elasticity of the trade index with respect to the job destruction rate implied by Figure 3 is –1.1 and the elasticity of the trade index with respect to the job acquisition proxy implied by Figure 4 is 0.9. Moreover, values of $\overline{R}^2$ for the regressions corresponding to Figures 3 and 4 are 0.11 and 0.15, respectively.

4-digit SIC categories, we regressed the trade index against both b and $\tilde{e}$ simultaneously for each year from 1973-1986. These results are reported in Tables 1 and 2. It is striking to observe that every estimated coefficient for b is negative, while every estimated coefficient for $\tilde{e}$ is positive.

In Table 3, we add a variety of observable and industry-specific and year-specific variables to the analysis to see if, after controlling for these characteristics, we can still observe a negative correlation between the trade index and the job destruction rate and a positive correlation between the trade index and the job acquisition rate.

The first variables to be added to the analysis are the one-period lagged rates of job acquisition and job destruction. Recall from our earlier description of the data that job destruction and job creation (from which our measure of job acquisition is constructed) are calculated based on March employment figures. By contrast, imports and exports are measured on a calendar-year basis. Furthermore, it may take some time before high job destruction rates are incorporated into the searching worker's decision-making process. We expect that the lagged rate of job acquisition should be positively correlated with the trade index, while the lagged rate of job destruction should correlate negatively with the current value of the trade index.

The remaining control variables can be divided into two groups. The first group contains two variables that are both time specific and industry specific. These variables are the amount of capital per worker (k_{it}) and production workers as a share of total employment $(prodworker_{it})$.[21]The second group consists of two variables that change over time, but are common to all sectors. The first is the overall rate of unemployment $(unemployment_t)$ and the

[21] 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

second is a trade-weighted index of the value of the dollar $(dollar_t)$, with higher values meaning that the dollar is stronger.[22]

Table 3 shows the results for regressions based on both the 2-digit and 4-digit sample of industries. Once again, all of the estimated coefficients on the job acquisition rate (both contemporaneous and lagged) are positive, while all of the estimated coefficients on the job destruction rate (both contemporaneous and lagged) are negative. Furthermore, all of the estimates for the impact of job destruction on the trade index are highly statistically significant, while half of the estimates for the impact of job acquisition are statistically significant. In terms of magnitude, the estimated coefficients imply an estimated elasticity with respect to the contemporaneous job destruction rate ranging between –0.5 and –0.9, while estimate for the elasticity with respect to the job acquisition rate ranges from 0.4 to 1.6.[23] By comparison, the estimated elasticity of the trade index with respect to the value of the dollar lies between 1.7 and 2.7.[24]

Clearly our small set of control variables cannot account for all industry-specific characteristics that might be related to trade and turnover. As such, we present the results from a regression model based on industry fixed effects in Table 4. While the magnitudes of the estimated coefficients are substantially reduced compared with the earlier estimates, the sign pattern remains the same (although none of the estimated coefficients on the job acquisition rate are statistically significant).

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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.

[22] 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.

[23] These estimates were calculated at the mean values of all variables. See footnote 20 for more information.

[24] Between 1973 and 1986 the G-10 index for the value of the dollar had an average value of 109 (author's calculations).

Finally, the DHS data separates the sample of two-digit industries into sub groups to examine the contribution to job creation undertaken by start-up firms relative to continuing firms, and to examine the magnitude of job destruction attributed to exiting firms relative to job destruction that occurs at establishments that continue to exist. We exploit this disaggregated data by looking at the impact on the trade index of b on and $\tilde{e}$ for continuing firms versus that for shut downs (the impact of b only) and that of new entrants (the impact of $\tilde{e}$ only). Our results are reported in Table 5.

With only four exceptions, all of which involve continuing firms, the sign patterns that emerged in the earlier explorations continue to show up in this more disaggregate analysis. One interesting point that emerges from Table 5 is that the magnitude of the effect is much larger for shut downs and new entrants than it is for continuing firms.

4. Conclusion.

Many of the leaders who shape public policy and guide public discourse tend to believe, without any real evidence, that exposure to international trade either creates jobs or destroys jobs. Those who argue in favor of freer trade generally tend to argue that trade creates jobs, while those opposed to freer trade argue the reverse.

On firmer logical ground, Bhagwati and Dehejia (1994) and Bhagwati (1998) have argued that lower transportation costs and greater ease of communication have created a world of "kaleidoscopic comparative advantage", and that greater openness to trade might create higher rates of job turnover.

Both of these arguments suggest a causal relationship between greater exposure to international trade and higher job turnover. In the first part of this paper, we present an alternative model of the link between turnover and trade. In our model, cross-sector and cross-country differences in international trade are an independent source of comparative advantage. The causation is reversed. Turnover creates a reason for trade. In particular, sectors with high job destruction or low job acquisition rates compared with other countries are likely to be at a comparative disadvantage, while sectors with low rates of job destruction and high rates of job acquisition are likely to have a comparative advantage.

We turn to the evidence in the second part of the paper. We merge the data constructed by Davis, Haltiwanger, and Schuh (1996) with trade data to look for correlations among trade, job destruction, and job acquisition. Our results are striking. We report on 48 different regressions that include 62 instances of current or lagged values of job destruction along with 62 instances of current or lagged values of job acquisition. We summarize the results in Table 6.

Based on our model, we expected to find a negative correlation between our trade index and job destruction, and a positive correlation between the trade index and job acquisition. The expected signs appeared in all but one case for job destruction, and all but 3 cases for job acquisition. Moreover, the coefficients on job destruction were statistically significant at conventional levels more than two thirds of the time. Statistical significance was a bit more elusive on the job acquisition variable, occurring in a bit under one third of the instances.

There are two problems with the empirical findings. The first is that we cannot distinguish between cause and effect. While we conducted the empirical work by putting the turnover variables on the right hand side of the equation, we cannot definitively assert that turnover causes trade.[25] In all likelihood, the causality is probably bi-directional.

[25] Perhaps one small piece of evidence supporting this direction of causality is that the lagged values of the turnover variables appeared in our regressions with the expected signs and, in many cases, were statistically significant.

The second problem is that the results are, in fact, too strong. Our model is based on a cross-country comparison of intersectoral differences in turnover. Our data only applies to the U.S. A more persuasive test of our model 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 U.S., there would be no independent influence of turnover on the pattern of trade.[26]

In any event, 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.

[26] 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.

Table 1
(Dependent Variable = *T*, results based on 2-digit SIC)

Year	Independent Variables $\tilde{e}_{it}$	b_{it}	$\bar{R}^2$
1973	0.544 (1.87)	-1.502 (-3.09)	0.445
1974	1.020 (2.90)	-0.620 (-1.55)	0.327
1975	1.054 (3.13)	-0.021 (-0.09)	0.314
1976	0.729 (1.25)	-0.189 (-0.24)	-0.018
1977	1.025 (2.83)	-1.276 (-2.63)	0.416
1978	0.979 (2.55)	-1.412 (-2.31)	0.351
1979	0.502 (1.356)	-1.399 (-2.79)	0.394
1980	0.738 (1.967)	-0.989 (-1.92)	0.292
1981	1.063 (2.32)	-0.708 (-1.28)	0.211
1982	0.909 (1.787)	-0.695 (-1.32)	0.173
1983	0.912 (1.55)	-0.596 (-1.36)	0.089
1984	0.434 (0.84)	-2.678 (-3.63)	0.433
1985	0.125 (0.295)	-2.009 (-5.55)	0.667
1986	0.987 (1.43)	-2.423 (-3.27)	0.415
1973-86	0.892 (6.76)	-0.578 (-5.60)	0.236

Notes: Estimated coefficients are listed in the body of the table, with *t*-statistics in parentheses. There are 19 observations in each year.

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

	Independent Variables		
Year	$\tilde{e}_{it}$	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 19 observations in each year.

Table 3
(Dependent Variable = *T*)

Independent Variables	Two Digit SIC (1)	(2)	(3)	Four Digit SIC (4)	(5)	(6)
$\tilde{e}_{it}$	0.663 (4.94)		0.436 (1.17)	1.802 (3.75)		1.066 (0.95)
$\tilde{e}_{i,t-1}$		0.664 (4.63)	0.302 (0.82)		1.753 (3.44)	0.908 (0.80)
b_{it}	-0.521 (-4.33)		-0.516 (-4.04)	-0.316 (-12.91)		-0.276 (-10.70)
$b_{i,t-1}$		-0.391 (-3.37)	-0.409 (-3.49)		-0.279 (-11.18)	-0.231 (-9.05)
k_{it}	-0.001 (-0.15)	0.001 (0.12)	-0.002 (-0.29)	0.008 (3.18)	0.008 (3.078)	0.006 (2.50)
$prodworker_{it}$	-0.322 (-6.15)	-0.341 (-6.11)	-0.250 (-4.46)	-0.346 (-21.87)	-0.352 (-21.12)	-0.331 (-19.91)
$unemployment_{it}$	1.360 (3.28)	1.023 (2.44)	2.090 (4.46)	0.890 (5.94)	0.770 (4.69)	1.311 (7.72)
$dollar_{it}$	-0.156 (-5.70)	-0.135 (-4.60)	-0.133 (-4.71)	-0.144 (-12.62)	-0.127 (-10.86)	-0.132 (-11.34)
$\bar{R}^2$	0.410	0.391	0.440	0.134	0.132	0.149
N	266	247	247	6258	5811	5811

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

Table 4
(Dependent Variable = *T*, Industry Fixed Effects)

Independent Variables	Two Digit SIC			Four Digit SIC		
	(1)	(2)	(3)	(4)	(5)	(6)
$\tilde{e}_{it}$	0.154 (0.70)		0.040 (0.186)	0.206 (0.45)		0.307 (0.64)
$\tilde{e}_{i,t-1}$		0.109 (0.50)	-0.028 (-0.13)		0.421 (0.90)	0.496 (1.02)
b_{it}	-0.130 (-1.78)		-0.206 (-2.85)	-0.030 (-2.88)		-0.046 (-4.27)
$b_{i,t-1}$		-0.190 (-3.23)	-0.240 (-4.02)		-0.037 (-3.69)	-0.047 (-4.62)
k_{it}	0.040 (3.24)	0.044 (3.49)	0.050 (3.96)	-0.004 (-1.29)	-0.005 (-1.48)	-0.002 (-0.51)
$prodworker_{it}$	1.012 (6.92)	1.180 (7.92)	1.079 (7.21)	0.253 (9.72)	0.269 (9.93)	0.124 (5.00)
$unemployment_{it}$	1.218 (5.87)	1.376 (7.31)	1.787 (7.66)	0.640 (11.57)	0.764 (13.13)	0.809 (12.90)
$dollar_{it}$	-0.113 (-8.03)	-0.097 (-6.91)	-0.102 (-7.38)	-0.117 (-27.28)	-0.115 (-26.91)	-0.121 (-28.08)
N	266	247	247	6258	5811	5811

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

Table 5
(Dependent Variable = T)

Independent Variables		Pooled Regressions (1)	(2)	(3)	Industry Fixed Effects (4)	(5)	(6)
Continuing Firms	$\tilde{e}_{it}$	0.103 (0.62)		-0.132 (-0.41)	0.164 (0.91)		-0.009 (-0.05)
	$\tilde{e}_{i,t-1}$		0.185 (1.04)	-0.002 (-0.01)		0.131 (0.69)	0.041 (0.23)
	b_{it}	-0.221 (-1.66)		-0.340 (-2.67)	0.047 (0.62)		-0.099 (-1.26)
	$b_{i,t-1}$		-0.076 (-0.56)	-0.070 (-0.50)		-0.045 (-0.64)	-0.050 (-0.74)
Shut Downs	b_{it}	-2.348 (-6.58)		-1.552 (-3.62)	-1.269 (-6.27)		-1.026 (-5.12)
	$b_{i,t-1}$		-2.018 (-5.28)	-1.536 (-3.55)		-0.943 (-4.68)	-0.838 (-4.15)
New Entrants	$\tilde{e}_{it}$	0.522 (3.38)		0.441 (2.38)	0.167 (1.78)		0.125 (1.38)
	$\tilde{e}_{i,t-1}$		0.450 (2.72)	0.397 (2.22)		0.151 (1.55)	0.118 (1.29)
k_{it}		-0.008 (-1.46)	-0.005 (-0.93)	-0.009 (-1.64)	0.039 (3.39)	0.043 (3.52)	0.048 (4.10)
$prodworker_{it}$		-0.266 (-5.25)	-0.302 (-5.54)	-0.205 (-3.75)	1.078 (7.84)	1.185 (8.20)	1.111 (7.97)
$unemployment_t$		1.501 (3.79)	0.585 (1.40)	1.807 (3.91)	1.333 (6.83)	1.166 (6.07)	1.654 (7.46)
$dollar_t$		-0.112 (-4.08)	-0.095 (-3.20)	-0.086 (-3.024)	-0.085 (-6.16)	-0.080 (-5.61)	-0.072 (-5.28)
N		266	247	247	266	247	247
$\bar{R}^2$		0.467	0.435	0.497			

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

Table 6

	Number of Occurrences
Estimated coefficient for *b* is negative and *p*-value $\leq$ 0.01	42
Estimated coefficient for *b* is negative and 0.01 < *p*-value $\leq$ 0.05	3
Estimated coefficient for *b* is negative and *p*-value > 0.05	16
Estimated coefficient for *b* is positive	1
Estimated coefficient for *e* is positive and *p*-value $\leq$ 0.01	10
Estimated coefficient for *e* is positive and 0.01 < *p*-value $\leq$ 0.05	8
Estimated coefficient for *e* is positive and *p*-value > 0.05	40
Estimated coefficient for *e* is negative	4

Notes: This table summarizes the findings for both current and lagged values of the respective variables, as well as the results reported in Table 5 where these variables are disaggregated into the components associated with continuing firms, shut downs, and new entrants. The p-value is 0.28 for the one case where the estimated coefficient for *b* is positive. The p-values are all above 0.68 for the three cases for which the estimated coefficient of *e* is negative.

Figure 1

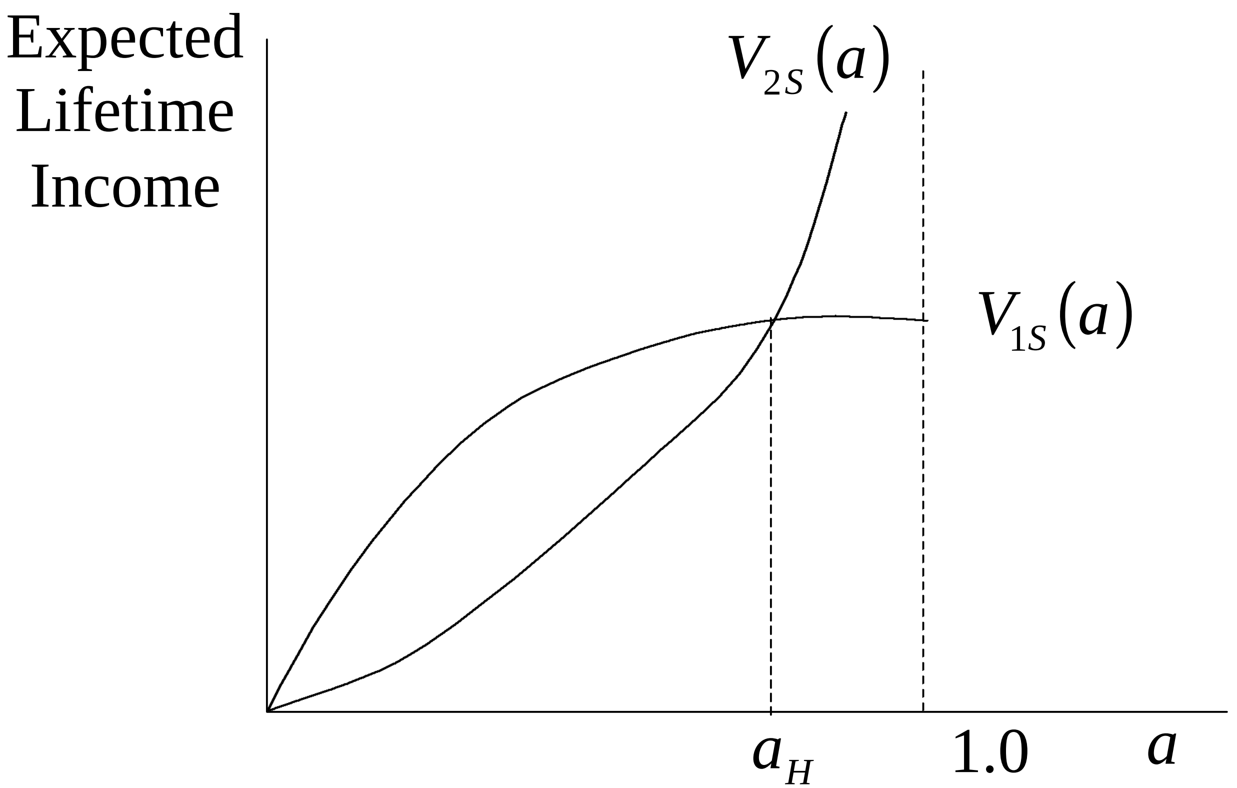


Figure 2

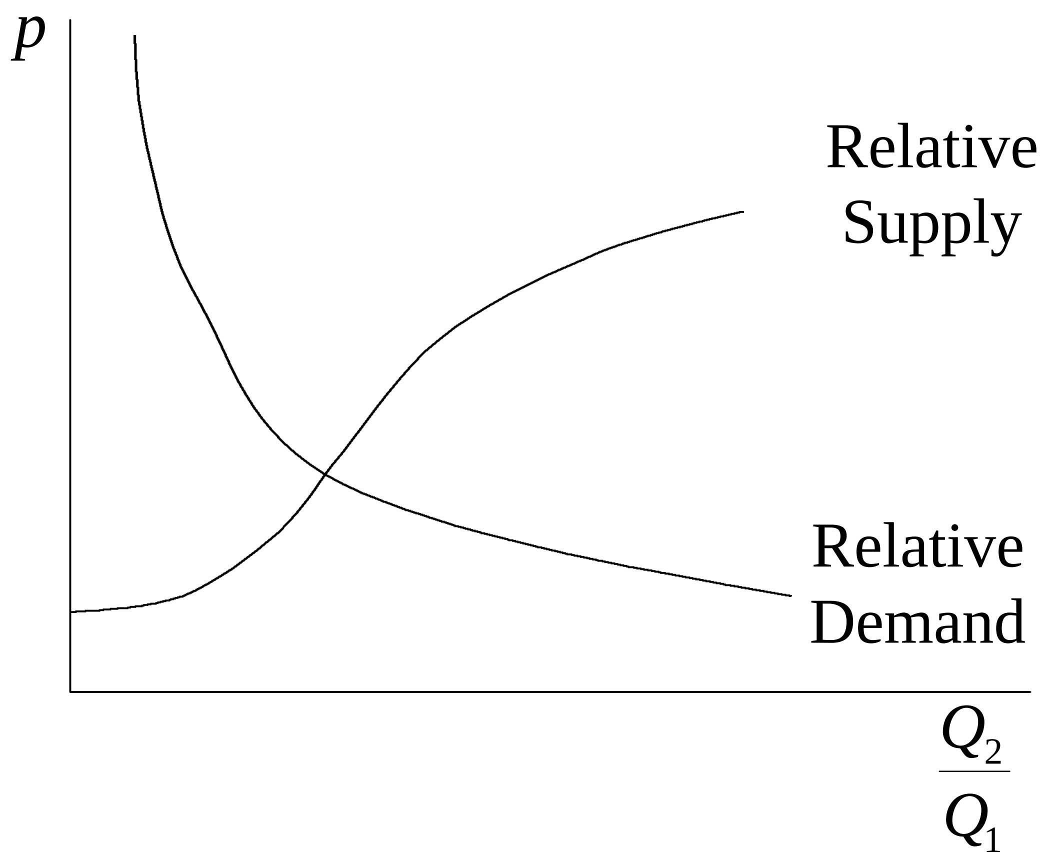


Figure 3

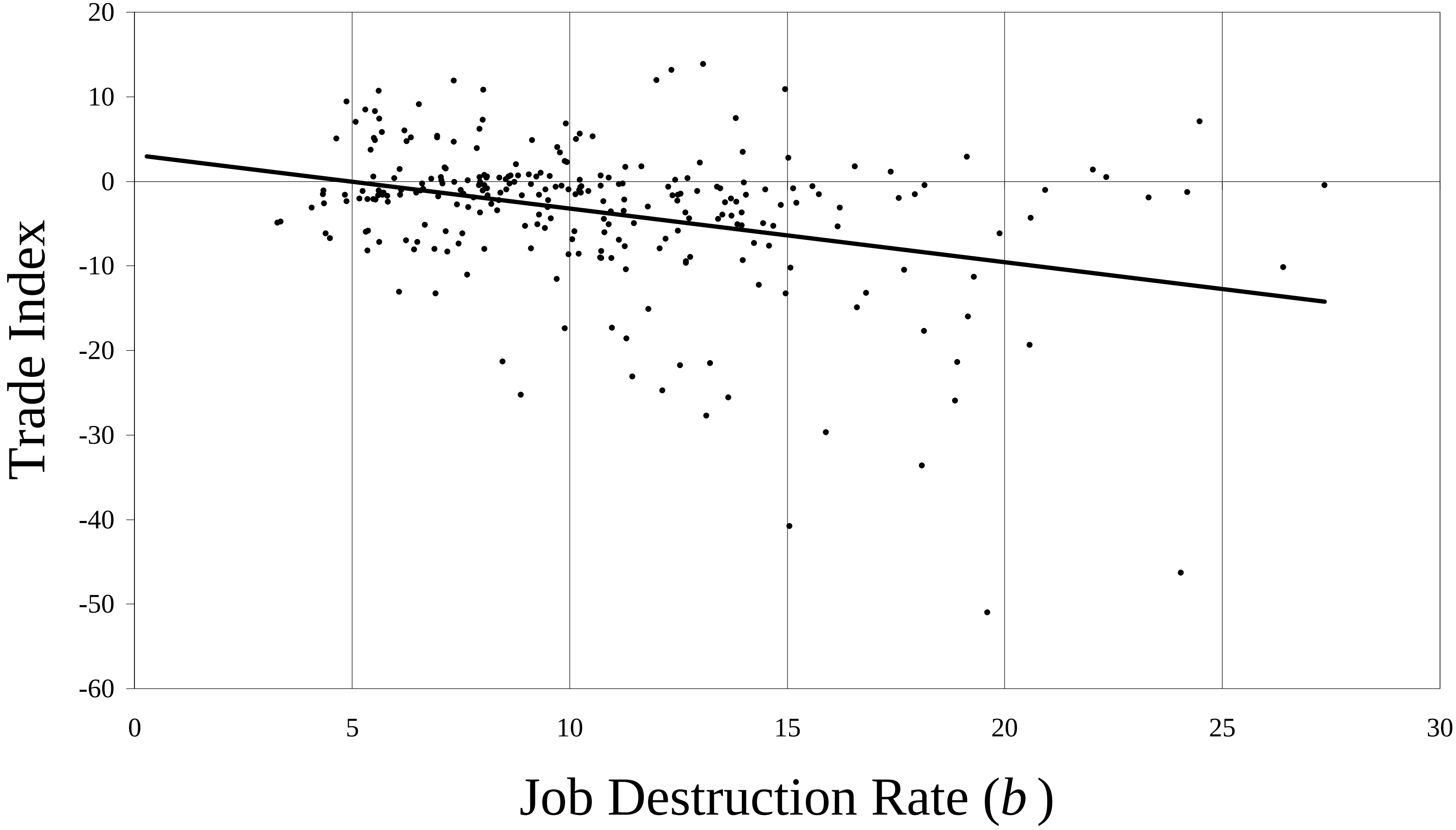
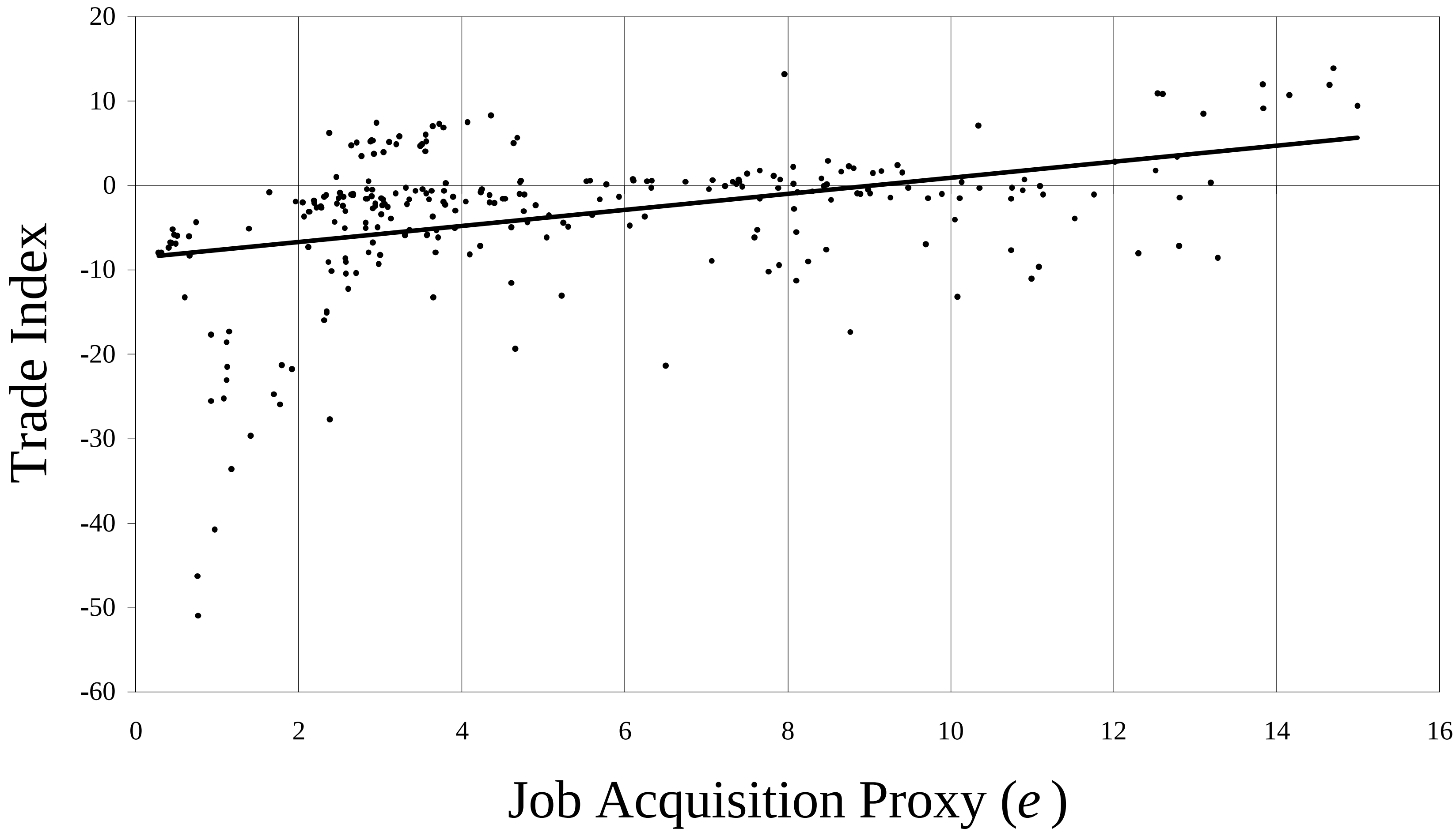

Trade Index
20
10
0
-10
-20
-30
-40
-50
-60
0
5
10
15
20
25
30
Job Destruction Rate (*b*)

Figure 4



20
10
0
-10
-20
-30
-40
-50
-60
0
2
4
6
8
10
12
14
16
Trade Index
Job Acquisition Proxy (*e*)