

**TRADE LIBERALIZATION AND INTER-INDUSTRY REALLOCATION  
IN INDONESIA**

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**VANDERBILT  
UNIVERSITY**

Economics Honors Thesis No. 2011-02

May 2011

DEPARTMENT OF ECONOMICS  
VANDERBILT UNIVERSITY  
NASHVILLE, TN 37235

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Senior Honors Thesis

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April 24, 2011

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First and foremost I would like to thank Professor Joel Rodrigue, without whom none of this would have been possible. My greatest thanks to Professor Mario Crucini as well, for numerous helpful suggestions along the way. I am indebted to the Vanderbilt Undergraduate Summer Research Program for their generous support of my research during the summer of 2010. And thank you to my fellow honors students, who helped shape the most significant academic experience of my life.

# 1 Introduction

Throughout the 1990s, the Indonesian government significantly reduced tariffs on a large number of imported goods, spanning virtually the entire manufacturing sector. For example, in 1995, upon becoming a member of the World Trade Organization, Indonesia made a commitment to lower tariffs on a wide range of products to 40 percent or less over the next ten years. This paper asks, did these tariff reductions cause the country to shift which industries it specializes in? If so, were the industries that were shifted toward more or less conducive to Indonesia's long-run economic development than the industries that were shifted away from?

This research is motivated by the potential links between trade policy and economic growth. Advocates of free trade hold that countries can always produce and consume more by specializing in the industries that they hold comparative advantages in, that developing countries can grow more quickly by increasing their investment rates by opening themselves up to cheaper first-world capital goods, and that developing countries can learn first-world technologies (and thereby grow faster) by importing intermediate, capital, and consumer goods from developed countries. Meanwhile, the infant industry argument, dating back to Alexander Hamilton, holds that in order for a country to develop, its government should (perhaps even must) shelter certain select industries until those industries can compete in the international marketplace. In his books *Kicking Away the Ladder* and *Bad Samaritans*, Ha-Joon Chang argues that such protectionism played a key part in the history of every currently-developed country's development, and

that no developing country will develop without following suit.

The relationship between international trade and economic growth might not be as simple as either of the above two viewpoints. In his *One Economics, Many Recipes*, Dani Rodrik argues that the relationship between trade and growth depends on context. He concludes, “whether trade liberalization promotes growth ... varies depending on whether the forces of comparative advantage push the economy’s resources in the direction of activities that generate long-run growth (via externalities in research and development, expanding product variety, upgrading product quality, and so on), or divert them from such activities” (p. 219). Our goal, then, is to determine whether the forces of comparative advantage pushed Indonesia, upon liberalizing trade, into specializing in industries with higher or lower growth potential than before.

## 2 Data

We use the *Statistik Industri*, the large- and medium-scale manufacturing survey conducted each year by the Indonesian Central Bureau of Statistics, *Budan Pusat Statistik* (BPS), covering the entire population of firms in the formal manufacturing sector of Indonesia that employ at least twenty people. The survey provides plant-level data on close to one hundred fifty variables each year, including revenues, intermediate inputs, employment, capital stocks, exports, imports, new financing, and five-digit ISIC codes for industrial classification. Each firm is tagged with an identifier variable, so that changes in each firm over time can be tracked. We have the data from the years 1990 to 2000,

covering more than fourteen thousand firms in 1990 and more than nineteen thousand firms in 2000.

The manufacturing data were combined with product-specific data on tariffs from Amiti and Konings (2007). The tariff rates imposed on each firm's output and inputs can be determined by matching the manufacturing data with the tariff data through the five-digit ISIC industry codes. Note that whereas our manufacturing data begins in 1990, the tariff data begins in 1991. As Figure 1 below shows, tariff rates dropped significantly for the majority of industries in Indonesia between 1991 and 2000. Tariff rates fell by different amounts for different industries during different years, which allows us to do the kind of analysis detailed below.

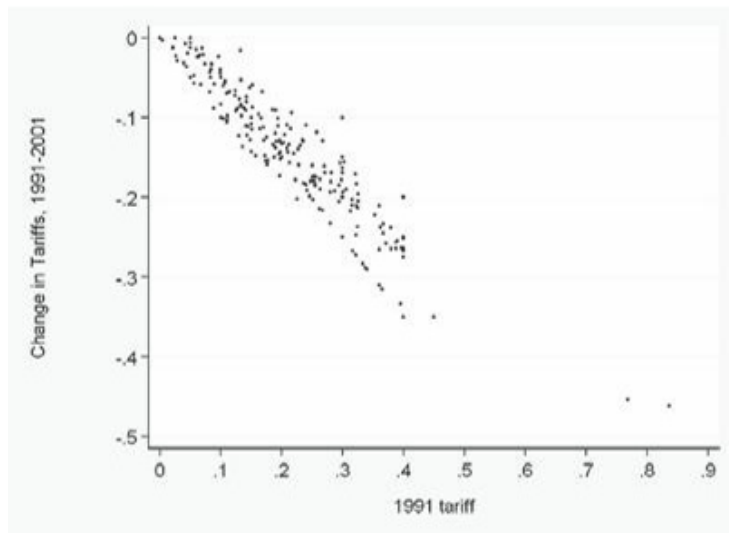


Figure 1: Change in tariffs, 1991-2001, relative to initial levels. Note: Industries that experienced an increase in their tariff over the sample period are excluded from this figure. These are industries 31161, 31169, 31310, and 31320. Source: *Amiti and Konings (2007)*.

## 2.1 Data construction

We had to go through several major steps to transform the data from their raw form into a usable form. Capital stock values were adjusted for inflation using methods similar to those of Appendix B in Blalock and Gertler (2004). Specifically, we used the *Indeks Harga Perdagangan Besar* (IHPB) (wholesale price indices), published monthly in BPS's *Buletin Statistik Bulanan Indikator Ekonomi* (Monthly Statistical Bulletin of Economic Indicators). The capital stock data, which are broken into categories for buildings and land, machinery, and vehicle fixed assets, were adjusted using the domestic price indices for construction materials, machinery, and vehicles, respectively. Unfortunately, the price indices break machinery into electrical versus nonelectrical machinery (without any price index for machinery in general), while the manufacturing data do not; the machinery price index we constructed was simply the sum of the two indices for electrical and nonelectrical machinery, divided by two.

The investment data are unfortunately not broken down in the same way (buildings and land vs. etc.). Therefore, we adjusted the values of investment using a firm-specific weighted price deflator, based on the average fractions of the firm's capital stock consisting of buildings and land, machinery, and vehicle fixed assets across all the years the firm existed in the dataset.

For several hundred firms in the 1991 data, the values of the subcategories of the capital stock did not sum to the total value of the capital stock that was given in the data, and/or the values of the subcategories of investment did not sum to the total value

of investment that was given in the data. We handled these problematic observations in the following step-by-step manner (note that the unifying logic behind all these steps is to replace certain data with certain other data whenever the former were in all likelihood the result of mis-typing the latter):

1. If the total given in the data equaled zero, but the calculated sum of the subcategories was not zero, and the number of non-zero subcategories was two or greater, then we replaced the total given in the dataset with the calculated sum of the subcategories.
2. If each subcategory had a value of zero, but the total given in the data was non-zero, then we kept the total as is but counted each of the subcategories as missing.
3. If the sum of the subcategories was  $10^n$  (for some integer  $n$ , possibly negative) times the total given in the data (i.e., if the two figures are the same except for extra/missing trailing zeroes), and if the number of non-zero subcategories was two or greater, then we replaced the total given in the dataset with the calculated sum of the subcategories.
4. Using a series of commands in Mathematica, we were able to find cases in which the total given in the data was equal to the sum of the subcategories, except with either one extra digit inserted, one digit deleted, two adjacent digits transposed with one another, or one digit replaced with another (e.g., an “8” replaced with a “3”). If one and only one of these was the case, and the number of non-zero



subcategories was two or more, then we replaced the total given in the dataset with the calculated sum of the subcategories.

5. For the capital stock data, we also used the 1992 total capital stock figures as a basis of comparison (for the firms that existed in 1992). (Note that there were no observations with these kinds of problems in 1992 or afterward.) If either the sum of the subcategories for 1991 or the total given in the 1991 data was within 15% of the total given in the 1992 data, then we went with the figure that was closer to the 1992 figure. In fact, if the total given in the 1991 data was within 15% of the 1992 figure, and the percentage by which the sum of the subcategories in 1991 was off was five or more times the percentage by which the total given in the 1991 data was off, then we went with the total given in the dataset and counted each of the subcategories as missing, even if the results of Step 4 told us to do otherwise. Note that in order to make these comparisons with the 1992 data, we first adjusted for inflation (see above). Note that for some of these firms, one of the values being compared (e.g., the 1992 total) was zero, meaning percentage differences were undefined, in which case our procedure was still the same, except replace “within 15%” with “within 20,000” and replace “the percentage by which ... was off” with “the amount by which ... was off.” Also note that we did not bother making comparisons with the 1992 data for the investment figures, since investment, unlike the value of the capital stock, is not expected to be approximately constant from year to year.
6. For any problematic observations that were not resolved through any of the above

steps, if the total given in the data and the sum of the subcategories were within 15% of each other, then we simply kept the data as is.

7. For any remaining discrepancies, we imputed the total values (see below).

The 1991 data also contained several hundred duplicate observations — duplicate in the sense that the values of all variables were the same, except for the numerical tag variable that identifies each specific firm. Other years also contained duplicate observations, although the number of duplicates significantly decreased each year. We handled these duplicate observations in two different ways: The first method was to replace, for each duplicate observation, the value of each variable with the mean of that variable for that industry during that year. The second method was to discard all duplicate observations and to perform all analysis using only industry-year means of variables, never totals. Our results do not appear to be sensitive to which of these two methods are used.

Note that the manufacturing data contain both current values and book values of fixed assets. We used the former rather than the latter as our operating definition of the value of a firm's capital stock. However, in 1991, 294 firms reported the total current value of their capital stock as zero while reporting a non-zero total book value of their capital stock. For these firms, we imputed the total current value of their capital stock (see below).

As described above, the value of the capital stock or investment (or both) needed to be imputed for the following observations: observations in which the values of the subcategories of the capital stock or investment did not sum to the total value of the

capital stock or investment that was given in the data, and in which Steps 1 through 6, described above, failed to resolve the discrepancy; and observations in which the current value of the capital stock was reported as zero while the book value of the capital stock was reported as non-zero. We imputed these values using Stata's *mi ice* command, which performs multiple imputation through chained equations. We regressed investment and the current value of the capital stock on the following independent variables: the firm's age; its number of employees; binary variables for whether or not the firm's ownership is more than ten percent foreign, whether or not the firm exports, and whether or not the firm imports any of its raw materials; and industry, year, and province dummies. We generated five imputed datasets.

For observations in which the industry did not exist within the dataset the previous year, it was of course impossible to calculate the change in the number of employees from the previous year. We handled these observations in two different ways: The first method was to count the number of employees the previous year as zero (in which case the change in the number of employees would be, by construction, the current number of employees). The second method was to throw that observation out as missing. The first method is the right one if the industry genuinely did not exist within Indonesia during the previous year, while the second method is the right one if the industry actually did exist within Indonesia during the previous year but, for one reason or another, none of the firms were surveyed. Our results do not appear to be sensitive to which of these two methods we use.

### 3 Empirical strategy

There are two ways in which tariff changes can affect people's decision of which industries to invest or work in: a *demand* effect and a *supply* effect, which run in opposite directions from one another. If Indonesia lowers its tariff on the product that an industry sells, then Indonesian firms in that industry are more exposed to competition from abroad, and therefore, *ceteris paribus*, investing or working in Indonesian firms in that industry is less attractive. If Indonesia lowers its tariffs on an industry's inputs, then costs decrease for Indonesian firms in that industry, and, *ceteris paribus*, investing or working in Indonesian firms in that industry is more attractive. As mentioned in Section 2, our tariff data include both the tariff rate on the product that each industry sells as well as a weighted average of the tariff rates on each industry's inputs; we can thereby examine both the demand-side effects and the supply-side effects of the tariff changes.

For each industry at each year, if we let  $TAR$  be the change, from the previous year to the current year, in the tariff on the product that an industry sells, then we more specifically define  $TAR$  as follows:

$$TAR = \log\left(\frac{\text{new tariff's price multiplier}}{\text{old tariff's price multiplier}}\right)$$

where a tariff's price multiplier is, for example, 1.25 if the tariff rate is 25%.

We analogously define  $ITAR$ , the change, from one year to the next, in the weighted average of the tariffs on an industry's inputs.

Note that investors and workers presumably react not only to tariff changes in an industry at an absolute scale, but also relative to what is happening in other industries

at that time. For each industry at each year, we define  $TAR_{rel}$  as the value of  $TAR$  for that industry, that year, divided by the average value of  $TAR$  that year. We define  $ITAR_{rel}$  analogously.

The manufacturing data allow us to use at least two different measures of which industries Indonesia is specializing in: the amount of investment in each industry and the number of employees in each industry. The manufacturing data also allow us to construct four different variables that plausibly have a significant positive impact on Indonesia's long-run economic development: capital intensity (the total value of an industry's capital stock divided by its number of workers), skill intensity (operationally defined as the fraction of an industry's workers that are educated — in the Indonesian context, we define “educated” to mean having a high school diploma or higher), spending on research and development (divided by the number of workers), and spending on human resources (worker training, etc.) (divided by the number of workers). We name these four variables  $K/L$ ,  $EDU$ ,  $R\&D$ , and  $HR$ , respectively.

We address our research question by running the regressions specified in Figures 2 and 3 below. Using each industry at each year as an observation, we regress investment (as in Figure 2) or the change in the number of employees from the previous year to that given year (as in Figure 3) on the four different measures of tariff changes (accounting for product vs. input tariffs and absolute vs. relative changes), as well as interaction terms between each of the four tariff change variables and each of the four development-related variables described above, controlling for industry and year fixed effects. Note that, for

each industry, we take  $K/L$  at its value in 1991,  $EDU$  at its value in 1996,  $R\&D$  at its value in 1994, and  $HR$  at its value in 1995. Ideally, in order to avoid endogeneity bias, we would take all four variables at their values in 1991, but each variable did not exist in the manufacturing data until those aforementioned years. ( $EDU$  actually could be calculated in 1995, but the 1995 educational data are missing for many firms, whereas the 1996 educational data are complete.)

The key coefficients of interest are the ones marked in red and blue in Figures 2 and 3 (namely,  $c_3$  through  $c_6$ ,  $c_8$  through  $c_{11}$ ,  $c_{13}$  through  $c_{16}$ , and  $c_{18}$  through  $c_{21}$ ). If these are negative, this implies that, within the context of Indonesia in the 1990s, freer trade spurred economic development, since a given decrease in an industry's product tariff is associated with a smaller shift out of that industry when the industry is more conducive to the country's development (with this conduciveness being proxied by  $K/L$ ,  $EDU$ ,  $R\&D$ , and  $HR$ ) than when the industry is less conducive to development, and a given decrease in an industry's average input tariff is associated with a larger shift toward that industry when the industry is more conducive to development than when less conducive. Similarly, if the signs are positive, this implies that, for Indonesia in the 1990s, freer trade retarded economic development. Note that this is all assuming that the signs on  $c_2$  and  $c_7$  are positive and that the signs on  $c_{12}$  and  $c_{17}$  are negative (i.e., decreases in product tariffs are associated with decreases in investment and employment, and decreases in input tariffs are associated with increases in investment and employment), as economic theory predicts, as explained above. If the sign on  $c_2$ ,  $c_7$ ,  $c_{12}$ , or  $c_{17}$  is the opposite of

this prediction, then the opposite logic applies to the interaction terms between that particular tariff change variable and the development-related variables.

We perform the above analysis at three different levels of aggregation (recall that the manufacturing and tariff data are matched through ISIC five-digit industry codes): five-digit industries, four-digit industries, and three-digit industries. Each year, there are approximately 300 five-digit industries, 110 four-digit industries, and 30 three-digit industries. An example of a three-digit industry is “furniture,” an example of a four-digit industry is “seats,” and an example of a five-digit industry is “seats, primarily with metal frames” (United Nations 2011). When examining different levels of aggregation, there is a tradeoff between data cleanliness and degrees of freedom: aggregating upward diminishes the influence of outlying observations but also lowers the total number of observations. In addition, varying the level of aggregation is of intrinsic interest, as different patterns of inter-industry reallocation might be observed at different levels of aggregation.

Even though we have manufacturing and tariff data from 1991 to 2000, we restrict our analysis to the years 1991 to 1996. The task of incorporating the years 1997-2000 is described in Section 5.

$$\begin{aligned}
& \text{investment} = c_1 + \\
& \text{TAR} \\
& \times [c_2 + c_3 K/L + c_4 EDU + c_5 R\&D + c_6 HR] \\
& \quad + \\
& \text{TAR}_{rel} \\
& \times [c_7 + c_8 K/L + c_9 EDU + c_{10} R\&D + c_{11} HR] \\
& \quad + \\
& \text{ITAR} \\
& \times [c_{12} + c_{13} K/L + c_{14} EDU + c_{15} R\&D + c_{16} HR] \\
& \quad + \\
& \text{ITAR}_{rel} \\
& \times [c_{17} + c_{18} K/L + c_{19} EDU + c_{20} R\&D + c_{21} HR] \\
& + \{\text{industry dummies}\} + \{\text{year dummies}\} + u
\end{aligned}$$

Figure 2: Regression with investment as the dependent variable. Each observation is an (industry, year)-pair.



$$\begin{aligned}
& \text{change in \# of employees} = c_1 + \\
& \text{TAR} \\
& \times [c_2 + c_3 K/L + c_4 EDU + c_5 R\&D + c_6 HR] \\
& \quad + \\
& \text{TAR}_{rel} \\
& \times [c_7 + c_8 K/L + c_9 EDU + c_{10} R\&D + c_{11} HR] \\
& \quad + \\
& \text{ITAR} \\
& \times [c_{12} + c_{13} K/L + c_{14} EDU + c_{15} R\&D + c_{16} HR] \\
& \quad + \\
& \text{ITAR}_{rel} \\
& \times [c_{17} + c_{18} K/L + c_{19} EDU + c_{20} R\&D + c_{21} HR] \\
& + \{\text{industry dummies}\} + \{\text{year dummies}\} + u
\end{aligned}$$

Figure 3: Regression with the change in the number of employees as the dependent variable. (Note: The only difference between this specification and the one in Figure 2 is the dependent variable.)

## 4 Results

The results of the analysis described above at the five-digit level of aggregation are displayed in Figures 4 and 5 below. None of the estimates of the coefficients are statistically significantly different from zero (not even at the .10-level). Note that these results were generated under the following specifications: the dependent variables were normalized by dividing investment each year by the 1991 capital stock and by dividing the change in the number of employees each year by the number of employees in 1991; logarithms were not taken of investment,  $K/L$ ,  $EDU$ ,  $R\&D$ , or  $HR$ ; duplicate observations were replaced with industry-year averages; and observations in which the industry did not appear in the data the previous year were counted as the industry having had zero employees the previous year.

We also ran other regressions (still at the five-digit level of aggregation), covering virtually every possible combination of the aforementioned options. We tried keeping the dependent variables as they were (rather than normalizing them); taking logarithms of investment,  $K/L$ ,  $EDU$ ,  $R\&D$ , and  $HR$  (which forced us to drop all observations in which any of those were zero, which were numerous); removing duplicate observations completely and running all analyses on mean levels of investment and employment changes for each industry, each year, rather than industry totals; treating observations in which the industry did not appear in the data the previous year as missing; and only using various subsets of the independent variables. We thereby ran a total of 112 regressions, 48 looking at investment and 64 looking at employment. For about two-thirds

of these alternative specifications, still none of the coefficients were statistically different from zero. Even for the other one-third, most of the coefficients were statistically indistinguishable from zero, and the ones that were not seemed to contradict each other, implying they were probably just noise rather than any real effect.

We repeated all of the above at the four- and three-digit levels of aggregation. The results of the regressions under the specifications described in the first paragraph of this section are given in Figures 6, 7, 8, and 9 below. The coefficients on  $TAR$ ,  $TARrel$ ,  $ITAR$ , and  $ITARrel$  are statistically significantly different from zero at the .05-level in Figure 6, as is the coefficient on  $EDU*ITARrel$  in Figure 9, but in the majority of regression specifications we ran, this was not the case. The overall picture that emerges from looking at the 112 regressions at the four- and three-digit levels of aggregation is much the same as the conclusion described above for the five-digit level: the tariff changes do not seem to be associated with any significant inter-industry reallocation.

Multiple-imputation estimates	Imputations	=	5
Linear regression	Number of obs	=	1345
	Average RVI	=	0.0000
	Complete DF	=	1053
	DF: min	=	1051.01
	avg	=	1051.01
DF adjustment: Small sample	max	=	1051.01
	F( 288, .)	=	.
Within VCE type: OLS	Prob > F	=	.

<u>investment</u>	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
TAR	-100.6499	322.26	-0.31	0.755	-732.9961	531.6964
K/L*TAR	.0004244	.0007809	0.54	0.587	-.0011079	.0019566
EDU*TAR	-746.3296	563.3051	-1.32	0.185	-1851.66	359.001
R&D*TAR	.0299158	.4490204	0.07	0.947	-.8511627	.9109943
HR*TAR	2.25309	1.579253	1.43	0.154	-.8457577	5.351938
TARrel	133.6499	323.7087	0.41	0.680	-501.5391	768.8388
K/L*TARrel	-.0003508	.0006581	-0.53	0.594	-.0016422	.0009406
EDU*TARrel	672.5023	566.5937	1.19	0.236	-439.2813	1784.286
R&D*TARrel	-.0337993	.4341964	-0.08	0.938	-.8857897	.8181911
HR*TARrel	-2.176102	1.574728	-1.38	0.167	-5.266072	.9138676
ITAR	130.7909	411.0063	0.32	0.750	-675.6954	937.2773
K/L*ITAR	-.0006175	.0012217	-0.51	0.613	-.0030147	.0017797
EDU*ITAR	988.9986	746.3616	1.33	0.185	-475.5298	2453.527
R&D*ITAR	-.0432081	.6430477	-0.07	0.946	-1.305011	1.218595
HR*ITAR	-3.106308	2.096091	-1.48	0.139	-7.219306	1.006691
ITARrel	-97.35688	417.3451	-0.23	0.816	-916.2812	721.5675
K/L*ITARrel	.0006787	.0012392	0.55	0.584	-.0017529	.0031103
EDU*ITARrel	-1196.999	764.3218	-1.57	0.118	-2696.77	302.7711
R&D*ITARrel	.0473526	.7133945	0.07	0.947	-1.352487	1.447192
HR*ITARrel	3.332642	2.160522	1.54	0.123	-.9067854	7.572069

Figure 4: Results of regression as specified in Figure 2, at five-digit level.

Multiple-imputation estimates	Imputations	=	5
Linear regression	Number of obs	=	1360
	Average RVI	=	0.0000
	Complete DF	=	1065
	DF: min	=	1063.01
	avg	=	1063.01
DF adjustment: Small sample	max	=	1063.01
	F( 291, .)	=	.
Within VCE type: OLS	Prob > F	=	.

<u>change # emp.</u>	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
TAR	25.07753	46.42962	0.54	0.589	-66.02658	116.1816
K/L*TAR	.0000754	.0001134	0.66	0.506	-.0001472	.000298
EDU*TAR	61.25708	81.25264	0.75	0.451	-98.17669	220.6909
R&D*TAR	-.0282281	.0652277	-0.43	0.665	-.1562179	.0997616
HR*TAR	.0264484	.2293175	0.12	0.908	-.4235179	.4764147
TARrel	-26.30376	46.66148	-0.56	0.573	-117.8628	65.25531
K/L*TARrel	-.000061	.0000956	-0.64	0.523	-.0002486	.0001266
EDU*TARrel	-56.73468	81.77508	-0.69	0.488	-217.1936	103.7242
R&D*TARrel	.0274376	.0630777	0.43	0.664	-.0963333	.1512086
HR*TARrel	-.0286262	.2286713	-0.13	0.900	-.4773246	.4200721
ITAR	-14.79392	59.19938	-0.25	0.803	-130.9548	101.367
K/L*ITAR	-.000121	.0001775	-0.68	0.496	-.0004692	.0002273
EDU*ITAR	-103.7141	107.6598	-0.96	0.336	-314.964	107.5358
R&D*ITAR	.0320182	.0934146	0.34	0.732	-.1512798	.2153161
HR*ITAR	.0934293	.304383	0.31	0.759	-.5038305	.6906891
ITARrel	14.75133	60.12368	0.25	0.806	-103.2232	132.7259
K/L*ITARrel	.0001232	.00018	0.68	0.494	-.0002301	.0004764
EDU*ITARrel	116.3448	110.2694	1.06	0.292	-100.0257	332.7152
R&D*ITARrel	-.030129	.103635	-0.29	0.771	-.2334813	.1732233
HR*ITARrel	-.2054063	.3137559	-0.65	0.513	-.8210575	.410245

Figure 5: Results of regression as specified in Figure 3, at five-digit level.

Multiple-imputation estimates	Imputations =	5
Linear regression	Number of obs =	555
	Average RVI =	0.0000
	Complete DF =	422
DF adjustment: Small sample	DF: min =	420.01
	avg =	420.01
	max =	420.01
Model F test: Equal FMI	F( 131, 420.0) =	1.99
Within VCE type: OLS	Prob > F =	0.0000

<u>investment</u>	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
TAR	-912.6488	399.5858	-2.28	0.023	-1698.086	-127.2117
K/L*TAR	.0014411	.0037417	0.39	0.700	-.0059136	.0087958
EDU*TAR	422.8303	668.8724	0.63	0.528	-891.924	1737.585
R&D*TAR	.5805662	1.814633	0.32	0.749	-2.986328	4.147461
HR*TAR	.0120621	1.959727	0.01	0.995	-3.840032	3.864156
TARrel	903.4685	400.8558	2.25	0.025	115.5351	1691.402
K/L*TARrel	-.0028459	.0035273	-0.81	0.420	-.0097792	.0040875
EDU*TARrel	-271.8476	674.733	-0.40	0.687	-1598.122	1054.427
R&D*TARrel	-.7793835	1.830862	-0.43	0.671	-4.378177	2.81941
HR*TARrel	.0680788	1.831687	0.04	0.970	-3.532336	3.668494
ITAR	942.2193	419.2778	2.25	0.025	118.0752	1766.364
K/L*ITAR	-.0011667	.0042363	-0.28	0.783	-.0094936	.0071602
EDU*ITAR	-605.0488	769.4105	-0.79	0.432	-2117.424	907.326
R&D*ITAR	-.3264474	2.073134	-0.16	0.875	-4.401457	3.748562
HR*ITAR	.141649	2.166516	0.07	0.948	-4.116916	4.400214
ITARrel	-880.8965	436.5064	-2.02	0.044	-1738.906	-22.88724
K/L*ITARrel	.0031145	.0042323	0.74	0.462	-.0052045	.0114336
EDU*ITARrel	269.6626	788.7622	0.34	0.733	-1280.751	1820.076
R&D*ITARrel	.9674878	2.295484	0.42	0.674	-3.544581	5.479557
HR*ITARrel	-.0202044	2.041272	-0.01	0.992	-4.032586	3.992177

Figure 6: Results of regression as specified in Figure 2, at four-digit level.

Multiple-imputation estimates	Imputations = 5
Linear regression	Number of obs = 555
	Average RVI = 0.0000
	Complete DF = 422
DF adjustment: Small sample	DF: min = 420.01
	avg = 420.01
	max = 420.01
Model F test: Equal FMI	F( 131, 420.0) = 1.87
Within VCE type: OLS	Prob > F = 0.0000

<u>change # emp.</u>	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
TAR	6.524038	50.42291	0.13	0.897	-92.58865	105.6367
K/L*TAR	.0000851	.0004722	0.18	0.857	-.000843	.0010132
EDU*TAR	-36.13649	84.40363	-0.43	0.669	-202.0426	129.7697
R&D*TAR	.1044318	.2289849	0.46	0.649	-.3456673	.5545308
HR*TAR	.0313217	.2472939	0.13	0.899	-.454766	.5174095
TARrel	-14.34043	50.58317	-0.28	0.777	-113.7681	85.08727
K/L*TARrel	-.0003808	.0004451	-0.86	0.393	-.0012557	.0004941
EDU*TARrel	78.55212	85.14318	0.92	0.357	-88.8077	245.9119
R&D*TARrel	-.1407074	.2310327	-0.61	0.543	-.5948317	.313417
HR*TARrel	-.0230423	.2311368	-0.10	0.921	-.4773713	.4312867
ITAR	-11.34595	52.9078	-0.21	0.830	-115.343	92.6511
K/L*ITAR	.0000319	.0005346	0.06	0.952	-.0010188	.0010827
EDU*ITAR	35.6825	97.09033	0.37	0.713	-155.161	226.526
R&D*ITAR	-.0556368	.2616045	-0.21	0.832	-.5698539	.4585803
HR*ITAR	-.0506768	.2733882	-0.19	0.853	-.5880563	.4867028
ITARrel	44.08209	55.08185	0.80	0.424	-64.18834	152.3525
K/L*ITARrel	.0003897	.0005341	0.73	0.466	-.0006601	.0014394
EDU*ITARrel	-116.0855	99.53229	-1.17	0.244	-311.7289	79.55799
R&D*ITARrel	.1606934	.2896625	0.55	0.579	-.4086753	.7300621
HR*ITARrel	.0052028	.2575839	0.02	0.984	-.5011114	.511517

Figure 7: Results of regression as specified in Figure 3, at four-digit level.

Multiple-imputation estimates	Imputations = 5
Linear regression	Number of obs = 150
	Average RVI = 0.0000
	Complete DF = 97
	DF: min = 95.06
	avg = 95.06
	max = 95.06
DF adjustment: Small sample	F( 46, .) = .
Within VCE type: OLS	Prob > F = .

<u>investment</u>	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
TAR	-2333369	2286610	-1.02	0.310	-6872827	2206090
K/L*TAR	.0003153	.0007762	0.41	0.686	-.0012256	.0018562
EDU*TAR	246.7266	183.4507	1.34	0.182	-117.4661	610.9193
R/D*TAR	-.0024845	.6725438	-0.00	0.997	-1.337642	1.332673
HR*TAR	-.0433116	.6812593	-0.06	0.949	-1.395771	1.309148
TARrel	2333376	2286609	1.02	0.310	-2206080	6872832
K/L*TARrel	-.0002751	.0007918	-0.35	0.729	-.001847	.0012968
EDU*TARrel	-260.9866	182.3343	-1.43	0.156	-622.9629	100.9897
R/D*TARrel	.0478655	.4401269	0.11	0.914	-.8258897	.9216207
HR*TARrel	.0125562	.6607139	0.02	0.985	-1.299116	1.324228
ITAR	2732375	2677491	1.02	0.310	-2583074	8047824
K/L*ITAR	-.0006786	.0012324	-0.55	0.583	-.0031252	.0017679
EDU*ITAR	-448.8607	265.5933	-1.69	0.094	-976.1257	78.40434
R/D*ITAR	-.0540074	.9395505	-0.06	0.954	-1.919236	1.811221
HR*ITAR	.1868507	1.023399	0.18	0.856	-1.844836	2.218538
ITARrel	-2732402	2677498	-1.02	0.310	-8047863	2583060
K/L*ITARrel	.0009739	.0014238	0.68	0.496	-.0018527	.0038004
EDU*ITARrel	439.3017	274.6959	1.60	0.113	-106.0342	984.6376
R/D*ITARrel	.0078181	.7365602	0.01	0.992	-1.454427	1.470063
HR*ITARrel	-.1450346	1.109089	-0.13	0.896	-2.346836	2.056767

Figure 8: Results of regression as specified in Figure 2, at three-digit level.



Multiple-imputation estimates	Imputations = 5
Linear regression	Number of obs = 150
	Average RVI = 0.0000
	Complete DF = 97
	DF: min = 95.06
	avg = 95.06
	max = 95.06
DF adjustment: Small sample	F( 46, .) = .
Within VCE type: OLS	Prob > F = .

<u>change # emp.</u>	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
TAR	546140.6	409922.1	1.33	0.186	-267651	1359932
K/L*TAR	.0001117	.0001392	0.80	0.424	-.0001645	.000388
EDU*TAR	-61.19937	32.88732	-1.86	0.066	-126.4884	4.089694
R&D*TAR	.1047566	.1205673	0.87	0.387	-.1345979	.3441111
HR*TAR	-.047024	.1221298	-0.39	0.701	-.2894803	.1954324
TARrel	-546138.8	409921.8	-1.33	0.186	-1359930	267652.3
K/L*TARrel	-.0001317	.0001419	-0.93	0.356	-.0004135	.0001501
EDU*TARrel	62.05719	32.68718	1.90	0.061	-2.834537	126.9489
R&D*TARrel	-.0658657	.0789018	-0.83	0.406	-.2225043	.090773
HR*TARrel	.0218192	.1184466	0.18	0.854	-.2133251	.2569635
ITAR	-639499	479995.5	-1.33	0.186	-1592403	313404.9
K/L*ITAR	-.0001261	.0002209	-0.57	0.569	-.0005647	.0003124
EDU*ITAR	80.19971	47.61308	1.68	0.095	-14.32343	174.7228
R&D*ITAR	-.1227136	.1684338	-0.73	0.468	-.4570943	.2116671
HR*ITAR	.0709703	.1834654	0.39	0.700	-.2932515	.4351921
ITARrel	639499.3	479996.7	1.33	0.186	-313406.8	1592406
K/L*ITARrel	.0001767	.0002552	0.69	0.491	-.0003301	.0006834
EDU*ITARrel	-98.70122	49.24491	-2.00	0.048	-196.4639	-.9385115
R&D*ITARrel	.0875406	.1320436	0.66	0.509	-.1745969	.3496782
HR*ITARrel	.0065746	.1988271	0.03	0.974	-.3881438	.401293

Figure 9: Results of regression as specified in Figure 3, at three-digit level.

## 5 Conclusions

We have not found any statistically significant effects of the 1990s tariff changes on investment or employment across industries in Indonesia, much less in any manner that has clear implications for the country's long-run economic development.

One possible explanation is that it may be unreasonable to expect investors or employers and employees to significantly respond to tariff changes within the space of a calendar year. A way to test this explanation would be to examine multi-year shifts in capital and labor, i.e., to run the same regressions as above, except rather than an observation consisting of the change in industry  $i$  from year  $j$  to year  $j + 1$ , an observation would consist of the change in industry  $i$  from year  $j$  to year  $j + k$ , where  $k > 1$ . Examining only single-year changes is particularly restrictive when one considers the fact that some tariff changes may have occurred late in the calendar year. In order to examine multi-year shifts but still have a satisfactory number of observations, it would be greatly beneficial to incorporate the years 1997-2000 into our analysis. Doing so raises two challenges. One is controlling for the effects of the 1997 East Asian financial crisis, which had an enormous impact on Indonesia's economy. A simple way of controlling for the crisis would be to include industry-specific crisis fixed effects, i.e., binary variables of the form {Industry  $i$  X Post-Crisis}, where 1991-1996 are pre-crisis years and 1997-2000 are post-crisis years. (Note that we already include year fixed effects in our analysis.) The second challenge is the fact that industries in the 1999 and 2000 datasets are labeled differently than in the other years. Incorporating those years would require either

establishing a correspondence between the two sets of labels, or pinpointing the firms' industries in 1999 and 2000 through some other method. One possibility is to match firms in 1999 and 2000 with their old selves in previous years through the firm-specific identification variable (and assume that the firms remained in the same industry), but since a significant fraction of shifts in industries from year to year consists of the exit and entrance of firms, this solution would not be particularly satisfactory.

If, even after incorporating the years 1997-2000 and examining multi-year shifts, there still do not appear to be significant effects of the tariff changes on reallocation of capital and labor across industries, another possible explanation is that credit constraints may have retarded reallocation: even when investors wanted to shift their investments in response to tariff changes, in some cases they may not have been able to do so due to a lack of access to credit. There are at least two ways to test this hypothesis. One is to examine only foreign investment, which in Indonesia is on average less credit-constrained. Another is to use data from Manova (2008) on different industries' varying levels of asset tangibility (a higher level of which makes it easier for firms to borrow) and dependence on external finance. We can include in our regressions interaction terms between those two variables and the four tariff change variables. The coefficients on the interaction terms could end up suggesting that, even if the tariff changes had insignificant effects overall, they had significant effects on industries of sufficiently high asset tangibility and/or low external finance dependence. (Note that the data from Manova (2008) are at the three-digit level, are from the U.S. rather than Indonesia, and are relative measures rather

than absolute. Using them is valid so long as the relative differences in asset tangibility and external finance dependence between different industries are roughly constant across countries.)

Another interesting possible further line of investigation would be to determine at what exact dates tariff changes were announced and enacted and then test for shifts in the stock prices of firms in the affected industries in response to tariff change announcements and enactments. Historical data are available for download from the Indonesia Stock Exchange (IDX), and information on tariff legislation is available from Indonesia's Ministry of Industry and Trade, but there would be considerable effort required to match the two sets of information. Also, there is unfortunately no way to match the firm-level stock data with our firm-level manufacturing data, as the latter do not include the identities of the firms.

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