

Exposure and Markups

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This article examines how to properly specify and test for factors that affect exchange-rate exposure. Starting from theoretical underpinnings and a sample of U.S. manufacturing industries between 1979 and 1995, we find that 4 of 18 industry groups are significantly exposed to exchange-rate movements through the effect of industry competitive structure, export share, and imported input share. On average, a 1% appreciation of the dollar decreases the return of the average industry by 0.13%. Consistent with our model's predictions, as an industry's markups fall (rise), its exchange-rate exposure increases (decreases).

Exchange-rate movements are an important source of risk for a firm. They affect a firm's expected cash flows and/or change the terms of competition for exporters, importers, and multinationals. Hung (1992) estimates that during the 1980s, U.S. manufacturing industries lost approximately \$23 billion/year, or 10% of total profits, due to the dollar's movements. Surprisingly, early studies which assume exchange-rate exposure to be constant [e.g., Jorion (1990), Bodnar and Gentry (1993) and Amihud (1994)] find that exchange rates have no effect on the stock returns of U.S. multinationals, exporters, or manufacturing industries. Recently, however, Allayannis (1997) and Bodnar, Dumas, and Marston (1998) examine time-varying exposure of industry returns.¹ In particular, the former article focuses on the effect the variation of U.S. industries' import and export shares have on exposure, while the latter focuses on pass-through and exposure in a sample of Japanese export-oriented industries.

Besides trade shares and pass-through, exchange-rate exposure also depends on the markup of an industry. Specifically, in industries with

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¹ Campa and Goldberg (1995, 1999) examine time-varying investment exposure.

oligopolistic market structure, in which the level of markup is high, firms can respond to exchange-rate fluctuations by altering the prices they charge locally and abroad. In these oligopolistic industries, therefore, we expect the effect of exchange-rate movements on returns to be small. In contrast, in industries where competition is intense, price must be set near marginal cost (hence the level of markup is low) and we expect the effects of exchange-rate movements on returns to be large.²

Campa and Goldberg (1995, 1999) are the first to consider the effect of markup on exposure. They examine how markup affects investment exposure. Specifically, Campa and Goldberg (1995) develop a model in which investment exposure is positively related to the export share and negatively related to the interaction of the markup and the share of production that is imported. They examine the predictions of their model using data on U.S. manufacturing industries at the two-digit SIC level and find that (i) investment exposure is time varying and (ii) in oligopolistic industries investment is significantly less affected by exchange-rate movements than in more competitive industries. Campa and Goldberg (1999) extend their analysis to include industries from Japan, Canada, and the United Kingdom.

Our work differs from Campa and Goldberg (1995, 1999) in the following ways. First, we focus on the effect of exchange-rate movements on stock returns rather than on investment. In efficient markets, stock returns should adjust instantaneously to an unexpected exchange-rate shock, while it takes a considerable amount of time for investment to adjust. This leads to different empirical specifications used to estimate investment and stock return exposure.³ Second, we consider industries at the four-digit SIC level. Our results suggest that there are differences across four-digit SIC industries within a two-digit SIC arising from differences in their trade shares and markups. Consequently examination of parameter estimates along with two-digit industry data on trade shares can mask the enormous difference in trade orientation of industries at the four-digit level of disaggregation. Third, we examine the impact of markups on accurately estimating exposure. We find that incorporating markups in the estimates of exposure improves the precision of the exposure estimates.

Recently, Bodnar, Dumas, and Marston (1998) examine the time-varying exposure of stock returns. They develop a model of imperfect competition where a local exporting firm competes against a foreign import-competing

² Although industry structure is not synonymous to price-over-cost markup (as demand, supply, and market structure all interact to determine price, quantity, and therefore markup), we interpret, as do Campa and Goldberg (1995, 1999), the markups to be correlated with the degree of competition. High markups correspond with more concentrated (oligopolistic) industries.

³ In particular, both expected and unexpected changes may affect investment, while only unexpected changes are important for stock returns. Also, theoretically, investment exposure is affected by the level of markup and the elasticity of markup (with respect to exchange rate changes), while stock return exposure is only affected by the level of markups.

firm in the export market. They derive firms' pass-through strategies and compute the resulting exposures for eight exporting Japanese industries, holding markups constant.

This article adds to the above literature by investigating how to properly specify and test for factors that affect exchange-rate exposure. We develop a theoretical model explicitly identifying the sources of exposure. Our modeling approach closely follows Campa and Goldberg (1995, 1999). In our model a firm uses imported inputs to produce output for sale both domestically and abroad. This framework highlights three key channels of exposure: (i) a positive effect through the competitive structure of the markets where final output is sold; (ii) a positive effect through the interaction of the competitive structure of the export market and the share of production that is exported; and (iii) a negative effect through the interaction of the competitive structure of the imported input market and the share of production that is imported. Our model formalizes the intuition that as an industry's markups fall (rise), its exchange-rate exposure increases (decreases).

We estimate the regression equation of exposure derived from our model using monthly data for 82 U.S. manufacturing industries at the four-digit SIC level, classified in 18 two-digit industry groups, between 1979 and 1995. This sample captures approximately half of the total annual trade of U.S. manufacturing industries. Similar to Campa and Goldberg (1995, 1999), we use the industry price-over cost markup, based on the methodology developed by Domowitz, Hubbard, and Peterson (1986), to characterize the industry structure of the final good. For the import side, we construct measures of imported inputs and imported input markups for our four-digit SIC industries. Each series is constructed using input-output table data to create appropriate weights so that imported inputs (imported input markups) is a weighted-average of imports (markups) of the industries that sell goods to (provide inputs into production for) a given industry. We are therefore able to have a measure of intermediate inputs and also distinguish between final goods and intermediate input markups at the four-digit SIC level.⁴

Empirical results suggest that 4 of 18 groups of the U.S. manufacturing industries are significantly affected by exchange-rate movements through at least one of the channels of exposure identified by our model. A 1% appreciation of the dollar reduces industry returns on average by 0.02% through the competitive structure of the final output good (channel a), reduces industry returns on average by 0.32% through the interaction of the industry structure of the export market and the share of production that is exported (channel b) and increases industry returns on average by 0.21% through the interaction of

⁴ Because the effects of exchange rates on returns are a function of the markups of the industry, and the markups themselves are functions of exchange rates and other factors that will influence exposure (e.g., imported intermediate costs), estimation of the return regressions must account for the endogeneity of markups with respect to exchange rates. We use an instrumental variables approach, described later in the empirical section, to handle the endogeneity of markups in the industry equilibrium.

industry structure of the imported input market and the share of production that is imported (channel c). Hence, in total, a 1% appreciation of the dollar reduces on average the returns of an industry by 0.13%.

Previous studies on exposure neglecting markups are missing the relevant contemporaneous effects of exchange rate movements on returns. When estimating exposure in a model that excludes markups, we find 3 of 18 groups have significant exposure and the level of significance has fallen. That is, previous studies overstate noise and understate the significance of exposure.

To quantify the increase in precision of including markups, we examine how markup volatility affects exposure estimates. If industry markups remain constant over time, then previous models of return exposure accurately estimate exposure, even though they do not explicitly account for their effect. Since data suggests that imported input and final goods markups vary over time (on average they vary by 25% of their mean value), we expect our model to estimate exposure more accurately than previous models. For industries with significant exposure and low variation in trade shares, but high volatility in markups, exposure is misestimated by 12.3% on average, when markup is not included. The average misestimation of exposure increases to 22% when exposure is estimated using the constant exposure model. Although these exposure differences can be large in percentage terms, the levels are not different by orders of magnitude (nor would one expect that from the theory). Nonetheless, these statistics suggest that incorporating markups in the measurement of exchange-rate exposure improves upon previous measures, when markups are volatile.

The remainder of the article is organized as follows: Section 1 describes the model; section 2 describes the empirical methodology and the data; section 3 presents the empirical tests and the results; and section 4 concludes.

1. The Model

This section develops a partial equilibrium model of a firm (industry) that allows us to analyze the effect of exchange rate movements on the firm's (industry's) rate of return. We begin by recalling that the rate of return for a firm is defined as

$$R_t = \frac{V_t - V_{t-1}}{V_{t-1}}, \quad (1)$$

where R_t is the rate of return for a firm at date t and V_t is the expected present discounted value of the firm at date t . We are interested in how movement in the exchange rate alters the firm's return. Given the definition above, this is directly linked with how the exchange rate affects V_t .

The expected present discounted value of the firm is based on the expected present discounted value of the firm's profit stream. Profit is a function of the firm's final good, which it sells both domestically and abroad, as well

as, imported intermediate inputs and capital which it uses in production.⁵ We assume the firm starts a period with a given capital stock (K), the current exchange rate (e) in home currency per unit of foreign currency, and current price of capital (r). The firm then chooses imports (M), and its capital stock for the following period (K'), to maximize the expected discounted value of its profits. The firm's value function can be written as follows:

$$V(K, e, r) = \max[pq(e, p) + ep^*q^*(e, p^*) - r[K' - (1 - \delta)K] - p_M M(e, p_M) + \rho EV(K', e', r')|e, r], \quad (2)$$

where $q(q^*)$ is the output of the final good sold domestically (abroad); the firm uses M and K to produce its total output $q + q^*$; $p(p^*)$ is the price of the output good in domestic (foreign) currency; p_M is the domestic price of imported intermediate inputs; δ is the depreciation rate of capital; ρ is the discount factor; and prime ($'$) denotes date $t + 1$ values. All output (or demand) functions depend on the respective price in each market and on the exchange rate.

The exchange rate affects expected profitability in three ways: (i) domestic market revenues, (ii) export market revenues, and (iii) imported intermediate input costs. The first way can be interpreted as capturing the possibility of import competition or the existence of wealth effects which potentially shift the demand schedule for domestically produced goods. These wealth effects are not only possible in the domestic final good sector, but also in the foreign final good and intermediate input sectors.⁶ With the exception of Campa and Goldberg (1999), other studies of exposure tend to ignore wealth effects.

This model assumes that the firm is a monopolist, taking its price as a function of its own output. Alternatively, we can think of the firm as being an oligopolist; if the firm is competing with others, then its price is a function of both its own and competitors' outputs. In the derivations below we treat the firm as a monopolist, but note that the results hold for other market structures as well. The only difference in the two market structures is that the terms below would be a function of other firms' output as well.⁷

To see the effect of exchange-rate movements on the rate of return of the firm, consider a Taylor series expansion of V_t around date $t - 1$ state

⁵ We abstract from domestic labor as an input into production. As long as the wage rate is independent of the exchange rate, this assumption does not affect our conclusions.

⁶ Froot and Stein (1991) account for wealth effects in foreign direct investment.

⁷ Marston (1996) and Bodnar, Dumas, and Marston (1998) consider duopoly settings. Their solution techniques differ from ours. They introduce a specific functional form for the utility (demand) function which they then use to substitute for all firms' prices (outputs) and reduce the profit, pass-through, and exposure equations to exogenous parameters. Alternatively, we have the other firms' output encompassed in our values of markups, revenues, etc.

variables. Equation (1) becomes

$$R_t = \frac{V_e * (e_t - e_{t-1})}{V_{t-1}} + \frac{V_r * (r_t - r_{t-1}) + V_K * (K_t - K_{t-1})}{V_{t-1}}. \quad (3)$$

The first term captures the effect of exchange-rate movements on the rate of return. The second term captures the effect of the capital stock and price of capital (the remaining state variables) on the rate of return. To examine the effect of exchange-rate movements on the rate of return, we apply the envelope theorem to our value function. To achieve this, assume movements in the exchange rate are permanent and uncorrelated over time and that expectations of the other state variables are equal to their current level. Solving the above problem results in the following equation (see Appendix A for a detailed exposition):

$$V_e = \frac{1}{1 - \rho} \left(\frac{pq + ep^*q^*}{e} \right) \xi \phi + \frac{1}{1 - \rho} \left(\frac{ep^*q^*}{e} \right) [1 + \xi] - \frac{1}{1 - \rho} \left(\frac{p_M M}{e} \right) \xi_M \phi_M, \quad (4)$$

where $\xi = \frac{p}{q} \frac{\partial q}{\partial p}$ and $\xi_M = \frac{p_M}{M} \frac{\partial M}{\partial p_M}$ represent the elasticity of demands for the domestic output and imported intermediate input, and $\phi = -\frac{e}{p} \frac{\partial p}{\partial e}$ and $\phi_M = -\frac{e}{p_M} \frac{\partial p_M}{\partial e}$ capture exchange-rate pass-through for the domestic output and imported intermediate input.⁸ The elasticity of demand is related to the firm's markup (price over cost margin) as defined by Domowitz, Hubbard, and Petersen (1986). Specifically the elasticity is the negative reciprocal of the price cost margin. The exchange-rate pass-through coefficients are comparable to pricing-to-market estimates in the literature.⁹ Their values determine whether changes in the local currency prices amplify or dampen the effect of an exchange-rate movement. Theory suggests that pass-through coefficients should be positive, $\phi > 0$ and $\phi_M > 0$ [see Campa and Goldberg (1999) for an overview]. Empirical studies find evidence consistent with this prediction [i.e., Knetter (1989) finds that German exporters to the U.S. stabilize while U.S. exporters amplify dollar prices].

The second term of our Taylor series expansion, Equation (3), can be proxied by the market return. Since exchange rates may have little effect on the market return [e.g., Jorion (1991)], we assume that the market return

⁸ We are not able to observe distinct markups for sales in domestic and foreign markets and therefore assume domestic and foreign markups of the final good are equal when deriving Equation (4). A similar restriction is faced by Campa and Goldberg (1999). Identical markups in the final goods markets implies a specific relationship between domestic and foreign pass-through that enables us to substitute out ϕ^* . See Appendix A for details.

⁹ Our pass-through terms are related to pricing-to-market since the latter estimates are motivated by first-order conditions of a monopolist selling to multiple export destinations where marginal cost is assumed equal in all destinations.

is only affected by our other state variables (r and K). If we assume that the effect of a change of the price of capital and capital stock affect a firm proportionally to that of the price of capital and capital stock affect a firm proportionally to that of the market as a whole, then, $R_t^m = V_r * (r_t - r_{t-1}) + V_K * (K_t - K_{t-1})$.

Combining the above expression with Equations (3) and (4) results in an equation linking exchange-rate movements with a firm's rate of return. The equation that we subsequently estimate is

$$R_t = a_0 + a_1 R_t^m + a_2 \frac{p_t q_t + e_t p_t^* q_t^*}{V_{t-1}} (\xi_t) \Delta e_t + a_3 \frac{e_t p_t^* q_t^*}{V_{t-1}} [1 + \xi_t] \Delta e_t + a_4 \frac{p_{Mt} M_t}{V_{t-1}} (\xi_{Mt}) \Delta e_t, \quad (5)$$

where $a_0 = 0$, $a_1 > 0$ is the constant of proportionality between the market and the firm, $a_2 = \frac{1}{1-\rho} \phi$, $a_3 = \frac{1}{1-\rho} > 0$, $a_4 = -\frac{1}{1-\rho} \phi_M$, and Δe_t is the percent change in the exchange rate between dates $t - 1$ and t . Equation (5) shows that exchange-rate movements affect a firm's size of the rate of return through trade shares, pass-through, and markups.¹⁰ First, we expect that on average, the share of domestic sales ($\frac{pq}{V_{t-1}}$) and the share of foreign sales ($\frac{ep^*q^*}{V_{t-1}}$) should positively affect the size of the rate of return, while the share of imported intermediate inputs ($\frac{p_M M}{V_{t-1}}$) should negatively affect the size of the rate of return. The larger the nominal value of trade shares, the larger the effect of exchange-rate movements on the size of the rate of return. Second, since, on average, pass-through (ϕ and ϕ_M) is found to be positive and less than unity [see, e.g., Knetter (1994)], pass-through dampens the effect of exchange rate movements on the size of the rate of return. This also implies that we expect, on average, $a_2 > 0$ and $a_4 < 0$.¹¹ Last, markups ($\frac{1}{\xi}$ and $\frac{1}{\xi_M}$) allow the firm to dampen the effect of exchange-rate movement on their rate of return. The larger the markup, the smaller the effect exchange-rate movements have on the size of the rate of return.

Equation (5) shows how exchange rate exposure is related to trade shares and markups. Exposure is measured as $[a_2 \frac{p_t q_t + e_t p_t^* q_t^*}{V_{t-1}} (\xi_t) + a_3 \frac{e_t p_t^* q_t^*}{V_{t-1}} [1 + \xi_t] + a_4 \frac{p_{Mt} M_t}{V_{t-1}} (\xi_{Mt})]$. This is the elasticity of the value of the firm with respect to the exchange rate. These three terms represent our three channels of exposure: channel (a) measures the competitive structure of the markets where the final output is sold, channel (b) captures export share and industry structure, and channel (c) measures imported input share and imported input competitive structure.

¹⁰ Marston (1996) and Bodnar, Dumas, and Marston (1998) do not find a direct link between markups and exposure. This is because these models do not allow for wealth effects.

¹¹ Here we assume pass-throughs to be constant, and hence embedded in the coefficients to be estimated, and focus on the effect of markups on exposure. In contrast, Bodnar, Dumas, and Marston (1998) assume markups are constant and focus on the effect of pass-through on exposure.

We now discuss details of the data and estimate the effect of exchange-rate movements on industry returns using a sample of U.S. manufacturing industries at the four-digit SIC during 1979–1995. The estimation provides us with a measure of how each of these channels affects the value of exposure.

2. Empirical Methodology and Data

There are two important econometric issues that we need to discuss before estimating Equation (5). First, both imported input markups and final good markups, along with exposure, are endogenous variables in the industry equilibrium. Therefore it would not be appropriate to use markups as exogenous independent variables in the regression equation. To address this issue we use an instrumental variables approach, in which we instrument markups using the current exchange rate and previous markups. We use exchange rates as an instrument since movements in exchange rates alter prices, which affect the price-cost margin. We also use past markups as an instrumental variable because they may provide important information to market participants about current markups. Also, lagged markups are suitable instruments, as they are likely uncorrelated with the error in the main regression.¹²

We assume that an industry’s total sales (at home and abroad) proxy for the value of the industry and define, therefore, trade shares relative to total sales. This is simply a normalization, similar in spirit to Campa and Goldberg (1995).¹³ This normalization, along with the common final goods markup and exchange rate variable, may increase the collinearity in the third and fourth terms of Equation (5), which represent exposure through the final output good side. To address this issue we combine those two channels in the estimation. Our estimation equation is therefore as follows:

$$\begin{aligned}
 R_{it} = & \beta_{0i} + \beta_{1i}R_t^m + \beta_2 \left[\underbrace{\left(\frac{1}{\widehat{MKUP}_{it}} \right)}_{\text{channel(a)}} + \underbrace{\left(\frac{X_{it}}{V_{it}} \right) \left(1 + \frac{1}{\widehat{MKUP}_{it}} \right)}_{\text{channel(b)}} \right] FXI_t \\
 & + \beta_3 \underbrace{\left(\frac{M_{it}}{V_{it}} \right) \left(\frac{1}{\widehat{IMKUP}_{it}} \right)}_{\text{channel(c)}} FXI_t + \epsilon_{it}, \tag{6}
 \end{aligned}$$

where R_{it} is the rate of return on the i th industry’s common stock adjusted for inflation at date t ; R_t^m is the rate of return on the market portfolio adjusted for inflation at date t ; FXI_t is the rate of return on a real dollar exchange

¹² Our results remain unaltered when we use imported intermediate input costs as an additional instrument.

¹³ See equations (10) and (11) in the aforementioned paper.

rate index;¹⁴ \widehat{MKUP}_{it} is the projected price cost markup of the final output good market of industry i at date t ; \widehat{IMKUP}_{it} is the projected imported input price cost markup of industry i at date t ; $\frac{M_{it}}{V_{it}}$ is the share of imported inputs in industry i at date t ; $\frac{X_{it}}{V_{it}}$ is the share of exports in industry i at date t .¹⁵

From Equation (6), an industry's exchange-rate exposure is affected by its competitive structure in the market where it sells its total production [third term; channel (a)], by the interaction of the competitive structure of the export market and the export share [fourth term; channel (b)], and by the interaction of competitive structure of the imported input market and its imported input share [fifth term; channel (c)]. The model predicts that markups have a positive effect through the total sales and exports ($\beta_2 > 0$) and a negative effect through imports ($\beta_3 < 0$).

Using the above specification, it is easy to see how previous models fit into our framework. If we assume that markups remain constant, then our model reduces to the model estimated by Allayannis (1997) in which exposure is only affected by the time variation of the import and export shares (markups are subsumed by the coefficients). If we further assume that import and export shares remain constant, then our model reduces to the model estimated by Jorion (1990), Amihud (1994), and others, in which exposure is assumed to be constant. Hence our model nests most models that have been used in the past to estimate exchange-rate exposure.¹⁶

2.1 The data

2.1.1 The sample. We estimate Equation (6), using data on a sample of 82 U.S. manufacturing industries at the four-digit SIC level. The list of industries is shown in Appendix B. We construct monthly industry returns from individual firm returns retrieved from the Center for Research and Security Prices (CRSP) database. Industry returns are the value-weighted average of the individual firm's return within the portfolio. The weights are the proportion of each firm's market capitalization in an industry's total capitalization. Dividends are included in the prices used to calculate firm returns. Firms are sorted into industry portfolios each month, according to their four-digit SIC and may enter or leave a given industry as they switch industries or cease to exist during the period that we examine (1979–1995). To adjust the

¹⁴ This specification assumes that exchange rates and stock prices follow a random walk process, hence the rate of return captures the unanticipated movements. In this framework, there is little difference between nominal and real exposure, since the largest percentage of variation comes from exchange rates rather than inflation. Similarly there is little difference in using excess returns (returns over the risk-free rate), since the variation in interest rates is also relatively small compared to the variation in exchange rates.

¹⁵ Using lagged trade shares in the estimation does not alter our results.

¹⁶ Formally, Dumas (1978), Hodder (1982), and Adler and Dumas (1984) define economic exposure to exchange rate movement as the regression coefficient of the real value of the firm (industry) on the exchange rate across states of nature.

nominal returns for inflation, we use the inflation index PUNEW (CPI-U) retrieved from CITIBASE. We also use the CRSP monthly value-weighted market index as our market portfolio.

2.1.2 The exchange-rate index. We use a real, trade-weighted monthly dollar index (RX-101) (i.e., in U.S. dollars per unit of foreign currencies) put forth by the Federal Reserve Bank of Dallas. This index employs moving-average trade weights based on annual trade flows of 101 U.S. trading partners. To test the sensitivity of our results to the exchange-rate index, we also use the JP Morgan real index, which contains a basket of 22 OECD and 23 emerging market currencies. We find that our results remain qualitatively similar. The use of an aggregate exchange-rate index, such as the Dallas Fed index, could potentially mask exposure, as industries may be very different with respect to the composition of their import and export trading partners. Goldberg and Tracy (1999) construct industry-specific import and export exchange-rate indices at the two-digit SIC level and find the majority of industry-specific exchange rates have correlations above 0.80 with the Dallas Fed index. The export exchange rates are more similar to the aggregate exchange-rate measure than are the import exchange rates. Specifically, the average correlation between the industry-specific export (import) exchange-rate indices and the Dallas Fed is 0.867 (0.768), while the median correlations are 0.895 and 0.815, respectively. These results suggest that the use of the aggregate real exchange-rate index in our tests is reasonable.

2.1.3 Imported input and export shares. We begin our construction of trade shares by using monthly values of U.S. manufacturing industry exports and imports with the world as a whole, at the four-digit SIC level. The source of this data is the Bureau of the Census U.S. Department of Commerce, Foreign Trade Division. Export prices used in the calculation of export values are the selling price, and include expenditures for freight, insurance, and other charges to the export point. The import data are based on Customs value, and the price used to calculate import values is generally defined as the price actually paid or payable for merchandise when sold for exportation to the United States, excluding U.S. import duties, freight, and other charges incurred in bringing the merchandise to the United States. The export (import) values that we use in this article are computed by the Bureau of the Census by multiplying the above export (import) prices by the quantities exported (imported).

The import data we obtain from the Bureau of the Census are values of imports of final goods to the United States for a given industry. Converting the data into imported inputs requires the use of the input-output tables from the 1987 Benchmark I-O Table at the six-digit level, available from the Bureau of Economic Analysis, to create appropriate weights. In particular,

we construct imported inputs into production using the following formula:

$$M_{kt} = \sum_{j=1}^N w_{kj} * IMPORTS_{jt}, \quad (7)$$

where, N is the total number of manufacturing industries at the four-digit level;¹⁷ w_{kj} is the percent of industry j 's output that is sold to industry k ; $IMPORTS_{jt}$ is the imports of final goods of industry j at date t ; M_{kt} is the intermediate imported inputs of industry k at date t .

That is, intermediate inputs of industry k (M_k) are a weighted average of all manufacturing imports. The weight associated with industry j 's imports (w_{kj}) is the percent of industry j 's total output sold to industry k .¹⁸ To our knowledge, this is the first article to construct imported inputs at the four-digit SIC level. In creating the weights we encountered bundling issues associated with the input-output data classification system differing from the SIC classification system at the four-digit level. This issue is discussed in Appendix C.

To construct the trade shares we also need data on industry value (to be used in the denominator). We proxy this by total sales (value of product shipment) that is available on an annual basis through the business article Census publication, Annual Survey of Manufactures. We construct the monthly imported input and export shares for each industry by dividing the constructed monthly industry imported input series and export series by one-twelfth of the annual value of product shipment. Where feasible, we cross-check whether the annual average of our constructed monthly imported input/export ratios match the annual ratios of each industry given in the publication U.S. Commodity Exports and Imports as Related to Output (this publication only reports annual trade shares). We find that they are very similar.

2.1.4 Markups. The final goods markup ($MKUP$) is the price-cost margin (PCM) proxying for industry competitiveness in the final goods sector. We follow the methodology developed by Domowitz, Hubbard, and Petersen (1986) to calculate PCMs at the four-digit SIC level, as follows:

$$PCM = \frac{\text{Value of sales} + \Delta\text{Inventories} - \text{Payroll} - \text{Cost of materials}}{\text{Value of sales} + \Delta\text{Inventories}}.$$

This is identical to (value added – payroll)/(value added + cost of materials), given the census' definition of value added. The data used to construct this measure are from the Census of Manufacturers and from the Annual Survey

¹⁷ We use three alternative measures of N : (i) we let N be the 82 four-digit SIC industries in our sample; (ii) we let N be the 82 industries plus all other manufacturing industries; and (iii) we let N be the 82 industries plus all other manufacturing plus all remaining imports. The three measures of imported inputs were highly correlated. We use the second method in this article.

¹⁸ Alternatively, one can use a weighting scheme derived from input cost data.

of Manufacturers published by the Bureau of the Census. Although we would like to construct monthly markup series for each U.S. manufacturing industry in our sample, most data is only available annually. We therefore calculate the markup with annual data and assume that monthly markups remain constant within a year and equal their annual markup.

Similar to Domowitz, Hubbard, and Petersen (1986), we find that within-industry markups vary and exhibit high and low markup periods. For example, the gypsum products industry (SIC 3275) had a markup of 0.387 in 1979, 0.230 in 1982, 0.42 in 1986, 0.22 in 1992, and 0.30 in 1995. A markup value of 0.387 means that the industry charges a price of approximately 38.7% above its marginal costs. For the U.S. manufacturing industries, we observe variability across time and across industry. In particular, the average markup for our sample of industries is 0.29 in 1979; it drops to 0.28 in 1982, rises to 0.30 in 1984, rises to 0.33 in 1989, and rises even further to 0.34 in 1995. The average standard deviation is 0.03.

We construct industry markups for the imported input market (*IMKUP*) using a methodology similar to the one used in constructing the imported inputs. In particular, we use the following formula to construct imported input markups:

$$IMKUP_{kt} = \sum_{j=1}^N w_{kj} * MKUP_{jt}, \tag{8}$$

where, N is the total number of manufacturing industries at the four-digit level; w_{kj} is the percent of industry k 's input costs that comes from industry j ; $MKUP_{jt}$ is the markup of industry j at date t ; and $IMKUP_{kt}$ is the imported input markup of industry k at date t .

Hence the imported input markups are the weighted-average industry markups, where the weights are the percentages of input costs across the industries which provide inputs into production for the industry at hand. The average imported input markup is 0.293 and its standard deviation is 0.0289. Similar to the final output markup, the average imported input industry markup varies over time ranging from 0.247 in 1982 to 0.325 in 1995.

3. Tests and Results

We estimate our regression equation for our sample of 82 U.S. manufacturing industries between 1979:1 and 1995:12. We implement a seemingly unrelated regression system (SUR) which can increase efficiency over the simple OLS by taking advantage of the possible cross-equation correlations in the error terms. We estimate a system of SURs for each industry at the two-digit SIC, by stacking the relevant industries at the four-digit SIC. For example, for the transport equipment industry (SIC 37), we estimate an SUR using the 8,

four-digit SIC industries, which comprise this industry.¹⁹ We constrain the coefficients to be the same for each channel of exposure across the sample of four-digit SIC industries within a two-digit SIC. This constraint may increase the precision of our exposure coefficients as there are now fewer coefficients to estimate.

Given that markups are endogenous in the industry equilibrium, we perform an instrumental variables approach described earlier. We find that our instruments of lagged markups and the current exchange-rate level trace the true series reasonably well. For example, the average adjusted R^2 for regressions on final goods markups is 0.47 and the average adjusted R^2 for regressions on imported input markups is 0.66. The average coefficient on the lagged markup for the regressions on final goods markups (imported input markups) is 0.625 (0.830) and all but five regression coefficients are statistically significant. The average coefficient on the exchange-rate level for the final goods markups regressions (imported input markups) is -0.00031 (-0.0125) and most are negative (i.e., 59 of 82 in the final goods markups regression) and significant (i.e., 58 of 82 in the final goods markups regression).²⁰

The coefficient values on lagged markups suggest that they have a strong influence on the level of the current markups. For the coefficients of exchange-rate levels, results suggest that a 1 standard deviation change in the level of the exchange rate accounts for 9% of the standard deviation in final goods markups and 37% of the standard deviation of the imported input markups.²¹ By introduction of the contemporaneous exchange rate, therefore, we make some progress in capturing markup volatility, although we do not have a true monthly markup series that corresponds to the estimation frequency.

3.1 The sign, level, and significance of exposure

Table 1 presents a summary of the results on the significance and signs of the exposures that are estimated with our model. Our model predicts that exposure is positively related to final goods markups through the total sales and the export share ($\beta_2 > 0$), and negatively related to intermediate inputs markups through the intermediate import share ($\beta_3 < 0$). This means that an appreciation of the dollar benefits the import side and the benefit is smaller

¹⁹ The industries are SIC 3711, motor vehicles and passengers cars; SIC 3714, parts of motor vehicles; SIC 3721, aircraft; SIC 3724, aircraft engines; SIC 3728, aircraft and spacecraft parts; SIC 3732, yachts and pleasure boats; SIC 3743, railway equipment and parts; SIC 3751, motorcycles, bicycles, and parts.

²⁰ The negative coefficient on the exchange rate can be explained as follows. Markup is the ratio of price to marginal cost. A rise in exchange rate will on average decrease both price and marginal cost, assuming positive pass-through on average. The negative sign is consistent with the effect of price on markups dominating the effect of marginal costs on markups.

²¹ The above calculation is done by multiplying the standard deviation of the exchange-rate level (8.8) by the average coefficient of the exchange rate level (i.e., -0.00031 for the regression on final goods markups) and expressing it as a percentage of 1 standard deviation of final goods markups.

Table 1
The significance and signs of the exposure

Exposure	# signif.	Total	Prediction	# signif.
β_2	4/18	4/18	(+)	4/4
β_3	2/18		(-)	2/2

This table summarizes the regression results of the exposure channels identified by our model defined in Equation (6): (i) the final good's markup and share of production that is exported (β_2) and (ii) the imported input industry markup and the share of imported inputs into production (β_3). The exposures are estimated for four-digit SICs at a two-digit level of aggregation during 1979–1995.

for higher markup (more oligopolistic) industries. An appreciation of the dollar hurts an industry's export side and total sales, and the reduction in returns is smaller for higher markup industries.

We find that in 4 of 18 industry groups, exposure is significant through the industries' export share and competitive structure of final output goods; and in 2 of 18 industry groups exposure is significant through the imported input share into production and imported input industry structure. Overall, 4 of 18 industry groups are significantly affected through at least one channel of exposure, indicating that the rate of return of approximately one in four U.S. manufacturing industry groups was significantly affected by exchange-rate movements during 1979–1995.

We also examine whether the signs of the exposure channels are in line with the signs predicted by our model and present results for each two-digit SIC group in Table 2, panel A. Although we find that only half of the industries at the two-digit SIC level have the correct sign of β_2 (positive), *all* industries that have a *significant* exposure through β_2 have the correct sign (four of four industries).²² The sign of the exposure through β_3 is negative in 14 of 18 industries at the two-digit level. Again, all industries at the two-digit SIC level that are significantly affected through this channel of exposure (two of two industries) have the correct sign.

Panel A of Table 2 also shows which industry groups are significantly affected by exchange-rate movements through at least one of the channels of exposure identified by our model and presents the average exposure at the two-digit SIC level. For each industry group at the two-digit level, we report the number of four-digit industries (column 3), the coefficient estimates with standard errors below them (columns 4 and 5), and the average level of exposure with standard deviations below (column 6). The furniture and fixture (SIC 25), chemicals (SIC 28), stone, clay and concrete (SIC 32), and industrial machinery and computers (SIC 35) industries are significantly

²² When we estimate the two channels of exposure [(a) and (b)] separately, we find 11 of 18 industry groups have the wrong sign on channel (a), two of which are significant. The standard error on this term is on average 10 times larger than the standard errors on channels (b) and (c). Large standard errors and wrong signs are often a sign of multicollinearity [see Greene (1990, p. 279)].

Table 2
Industry exposure

Industry	Name	# obs.	β_2	β_3	Exposure
Panel A. Regression model with markups 1979:01–1995:12					
SIC 20	Food and kindred products	5	0.009 (0.008)	-0.010 (0.013)	0.048 (0.060)
SIC 21	Tobacco	3	-0.001 (0.011)	-0.009 (0.034)	-0.105 (0.039)
SIC 22	Textile mill	4	-0.003 (0.007)	-0.001 (0.002)	-0.215 (0.096)
SIC 23	Apparel and other clothes	4	-0.007 (0.016)	-0.002 (0.003)	-0.523 (0.106)
SIC 24	Lumber and wood	3	0.007 (0.006)	-0.001 (0.004)	0.333 (0.112)
SIC 25	Furniture and fixture	2	0.004** (0.002)	-0.040*** (0.016)	-0.440 (0.411)
SIC 27	Printing and publishing	6	-0.001 (0.012)	-0.016 (0.012)	-0.214 (0.105)
SIC 28	Chemicals	14	0.002** (0.001)	0.000 (0.001)	0.163 (0.097)
SIC 29	Petroleum refining	1	0.033 (0.023)	-0.460 (0.416)	0.266 NA
SIC 31	Leather and leather products	4	0.008 (0.008)	-0.009 (0.007)	-0.249 (0.281)
SIC 32	Stone, clay and concrete	4	0.027** (0.012)	-0.057** (0.028)	-0.014 (0.252)
SIC 33	Primary metals	3	0.011 (0.008)	-0.020 (0.013)	-0.042 (0.324)
SIC 34	Fabricated metal products	3	-0.006 (0.008)	0.034 (0.023)	0.192 (0.126)
SIC 35	Industrial machines and computers	9	0.003** (0.001)	-0.008 (0.012)	0.255 (0.152)
SIC 36	Electronic equipment	4	-0.000 (0.002)	-0.001 (0.002)	-0.119 (0.148)
SIC 37	Transport equipment	8	-0.001 (0.001)	-0.003 (0.007)	-0.121 (0.022)
SIC 38	Instruments	2	-0.007 (0.011)	0.034 (0.041)	0.018 (0.007)
SIC 39	Miscellaneous	3	-0.000 (0.007)	-0.003 (0.005)	0.101 (0.146)
Panel B. Regression model without markups 1979:01–1995:12					
SIC 20	Food and kindred products	5	0.042 (0.050)	-0.016 (0.065)	0.100 (0.107)
SIC 21	Tobacco	3	-0.001 (0.026)	-0.024 (0.082)	-0.098 (0.039)
SIC 22	Textile mill	4	-0.022 (0.043)	-0.006 (0.010)	-0.193 (0.158)
SIC 23	Apparel and other clothes	4	-0.028 (0.075)	-0.011 (0.011)	-0.493 (0.106)
SIC 24	Lumber and wood	3	0.032 (0.053)	0.003 (0.028)	0.290 (0.101)
SIC 25	Furniture and fixture	2	0.017** (0.008)	-0.162** (0.065)	-0.428 (0.412)
SIC 27	Printing and publishing	6	0.001 (0.036)	-0.053 (0.034)	0.077 (0.035)
SIC 28	Chemicals	14	0.009 (0.005)	0.001 (0.003)	0.146 (0.099)
SIC 29	Petroleum refining	1	0.414 (0.259)	-1.909 (1.637)	0.315 NA

Table 2
(continued)

Industry	Name	# obs.	β_2	β_3	Exposure
SIC 31	Leather and leather products	4	0.038 (0.035)	-0.030 (0.021)	-0.234 (0.252)
SIC 32	Stone, clay and concrete	4	0.101** (0.042)	-0.155** (0.070)	-0.058 (0.310)
SIC 33	Primary metals	3	0.104 (0.063)	-0.090 (0.059)	0.289 (0.307)
SIC 34	Fabricated metal products	3	-0.026 (0.033)	0.130 (0.089)	0.241 (0.122)
SIC 35	Industrial machines and computers	9	0.012** (0.005)	-0.025 (0.041)	0.218 (0.152)
SIC 36	Electronic equipment	4	0.001 (0.007)	-0.004 (0.006)	-0.071 (0.160)
SIC 37	Transport equipment	8	-0.005 (0.006)	-0.008 (0.025)	-0.153 (0.046)
SIC 38	Instruments	2	-0.019 (0.030)	0.088 (0.096)	0.085 (0.036)
SIC 39	Miscellaneous	3	0.002 (0.026)	0.008 (0.015)	0.128 (0.122)

This table summarizes the regression coefficients and exposure level when we constrain the exposure coefficients β_2 and β_3 to be the same across four-digit industries within the same two-digit SIC. We present the number of industries in a two-digit SIC regression, the coefficient values (standard errors) and level of exposure (standard deviation) for our model that includes markups (panel A)

$$R_{it} = \beta_{0i} + \beta_{1i}R_{it}^m + \beta_2 \left(\frac{1}{MKUP_{it}} + \frac{X_{it}}{V_{it}} * \left(1 + \frac{1}{MKUP_{it}} \right) \right) FXI_t + \beta_3 \left(\frac{M_{it}}{V_{it}} * \frac{1}{MKUP_{it}} \right) FXI_t + \epsilon_{it}$$

and for a model that excludes markups (panel B)

$$R_{it} = \beta_{0i} + \beta_{1i}R_{it}^m + \beta_2 \left(\frac{X_{it}}{V_{it}} \right) FXI_t + \beta_3 \left(\frac{M_{it}}{V_{it}} \right) FXI_t + \epsilon_{it}$$

Average R^2 of 0.39 (0.38) and average DW of 2.05 (2.06) for the regressions in panel A (panel B). *** and ** denote significantly different from zero at the 1% and 5% level, respectively.

affected through the total sales, export share, and competitive structure of the final output good (β_2 significant), while the furniture and fixture (SIC 25) and stone, clay and concrete (SIC 32) industries are also significantly affected through the imported input share and the imported input competitive structure (β_3 significant).^{23,24}

We calculate exposure at the two-digit SIC level as an average of the underlying four-digit SIC industries' time-series average exposure. Each four-digit SIC industry's exposure at time t is defined as $\left[\beta_2 * \left(\frac{1}{MKUP_{it}} \right) + \beta_2 * \left(\frac{X_{it}}{V_{it}} \right) \left(1 + \frac{1}{MKUP_{it}} \right) + \beta_3 * \left(\frac{M_{it}}{V_{it}} \right) \left(\frac{1}{MKUP_{it}} \right) \right]$. The average level of exposure for the furniture

²³ We also test whether the two exposure coefficients (β_2 and β_3) are jointly significant and find this to be true for all industries that have at least one exposure coefficient significant, except for the industrial machinery and computers industry (SIC 35), for which exposures are not jointly significant. On the other hand, the fabricated metal products industry (SIC 34), which has no exposure coefficient individually significant, has exposure coefficients jointly significant (at the 10% level). When we include the market factor in these joint tests, we find in all of our regressions that we can reject the hypothesis that all three coefficients are jointly equal to zero. As expected, the market factor is highly significant in all of our regressions.

²⁴ We test for autocorrelation in the errors by using the Durbin-Watson test. On average, for our 18 SURs, the Durbin-Watson is 2.05. A Durbin-Watson statistic of close to 2 is evidence against the presence of autocorrelation. Table 2, panel A also reports the average R^2 as a measure of the overall fit of our model; the average R^2 is 0.39.

and fixture industry (SIC 25) is -0.440 , indicating that a 1% appreciation of the dollar increases its returns by 0.440%. Note that the standard deviation is fairly large (0.411), indicating that the two four-digit industries that comprise industry 25 have very different exposures. This divergence in exposures for industries at the four-digit SIC within a two-digit industry group is generally present across most industries and reflects the divergent trade shares and markups across those industries. For example, the correlation between net exports for the two four-digit industries that comprise industry 25 is 0.36, while the average correlation for the 14 four-digit industries that comprise the chemicals industry (SIC 28) is 0.07. Within this industry group, the correlations among several four-digit industries are negative and have large magnitudes (e.g., -0.53 between SIC 2812 and SIC 2892, and -0.58 between SIC 2833 and SIC 2821). This result suggests that the examination of parameters estimated along with two-digit industry data on trade shares could mask the differences in trade orientation of industries at the four-digit level of disaggregation.

To examine whether markups allow for a more precise estimation of exposure, we also present results of the estimation of a system of equations, where only trade shares vary with time.²⁵ Table 2, panel B presents exposure coefficients and levels across the 18 industry groups. Note that the difference in exposure coefficients between panels A and B reflects that panel B embeds the average markup in the estimate, that is, when excluding markups, the parameter estimate should be interpreted as a product of the true parameter and the markup level. Using a specification that only accounts for trade shares (and excludes markups), we find 3 of 18 industry groups are significantly exposed to exchange rates. This contrasts with 4 of 18 industry groups that are significantly exposed to exchange rates when we include markups (industries within SIC 28 are not affected by exchange rate movements when markups are excluded). In addition, the precision of the estimates is higher when we include markups in the specification, as reflected by the smaller standard errors (and therefore higher t -statistics).

Although the precision of the estimates is higher in the specification including markups, the majority of the values of exposure do not differ substantially across the two models (nor would we expect orders of magnitude of differences, based on theory). For example, the furniture and fixture industry (SIC 25) has an exposure of -0.440 when we include markups compared with -0.428 when we do not. On average, the absolute value of exposure across all 18 industry groups is 0.189 for the model that includes markups

²⁵ This system of equations is the one run by Allayannis (1997):

$$R_{it} = \beta_{0i} + \beta_{1i}R_t^m + \beta_2 \left(\frac{X_{it}}{V_{it}} \right) FXI_t + \beta_3 \left(\frac{M_{it}}{V_{it}} \right) FXI_t + \epsilon_{it}, \quad t = 1, \dots, T \quad i = 1, \dots, n,$$

where all the variables are as defined in the previous section.

and 0.201 for the model that only includes trade shares, and 0.218 versus 0.235, respectively, for the significantly exposed industries.²⁶

Bodnar and Gentry (1993) also examine U.S. industry return exposure.²⁷ They, however, examine exposure at the two-digit SIC level using a constant exposure model between 1979 and 1988. Their results suggest SICs 23, 29, and 37 are significantly affected during this period. These industries are not significant based on our results.²⁸ The difference in significant industries can be attributed to the use of a different model and/or to the use of a different level of data disaggregation. Comparing our results with Campa and Goldberg (1995), although they focus on investment exposure and use data at the two-digit level, we find similarly, differences across high- and low-markup industries. They find that high-markup industries have lower values of investment exposure than low-markup industries. We find the average return exposure of a high-markup industry is also lower than the average return exposure of a low-markup industry (−0.00037 and −0.04, respectively).

3.1.1 The time variation of exposure. Focusing on the industries that are significantly exposed to exchange-rate movements (SICs 25, 28, 32, and 35), we calculate the exposures for each of the underlying four-digit SIC industries over time. Specifically we calculate exposures by multiplying the estimated exposure coefficients by the respective variables for each channel of exposure, and sum up $[\beta_2 * (\frac{1}{MKUP_{it}}) + \beta_2 * (\frac{X_{it}}{V_{it}})(1 + \frac{1}{MKUP_{it}}) + \beta_3 * (\frac{M_{it}}{V_{it}})(\frac{1}{IMKUP_{it}})]$. Table 2 shows that there are two industries at the four-digit SIC level (SICs 2515 and 2599) included in SIC 25, 14 industries in SIC 28, 4 industries in SIC 32, and 9 industries in SIC 35. Figure 1 presents the monthly total exposure for a few of these 29 four-digit SIC industries between 1979 and 1995, along with their 95th percentile confidence intervals.²⁹ These graphs highlight four points. First, exposure is economically meaningful. The average exposure is 0.126 and the maximum (minimum) average exposure is 0.59 (−0.73). This means that a 1% appreciation of the dollar reduces industry returns by 0.126% on average. Second, exposure is time varying. Third, exposure differs substantially among industries at the four-digit level due to differences in trade shares and markups. This implies that estimating exposure at the two-digit level could mask differences at the four-digit level. Last, exposure is significantly different from zero over time.

²⁶ There are, however, a few industries for which exposure differs substantially. For example, the printing and publishing industry (SIC 27) has exposure of −0.214 when markups are included and 0.077 when they are not.

²⁷ Bodnar, Dumas, and Marston (1998) examine return exposure for a sample of Japanese industries.

²⁸ When we reestimate our model for the 1979–1988 period to match the Bodnar and Gentry (1993) time period, we find that industries with SICs 20, 32, and 35 are significantly affected through at least one of the exposure channels at the 5% significance level and industries with SICs 24, 25, and 28 at the 10% level.

²⁹ See Allayannis and Ihrig (2000) for a complete set of graphs.

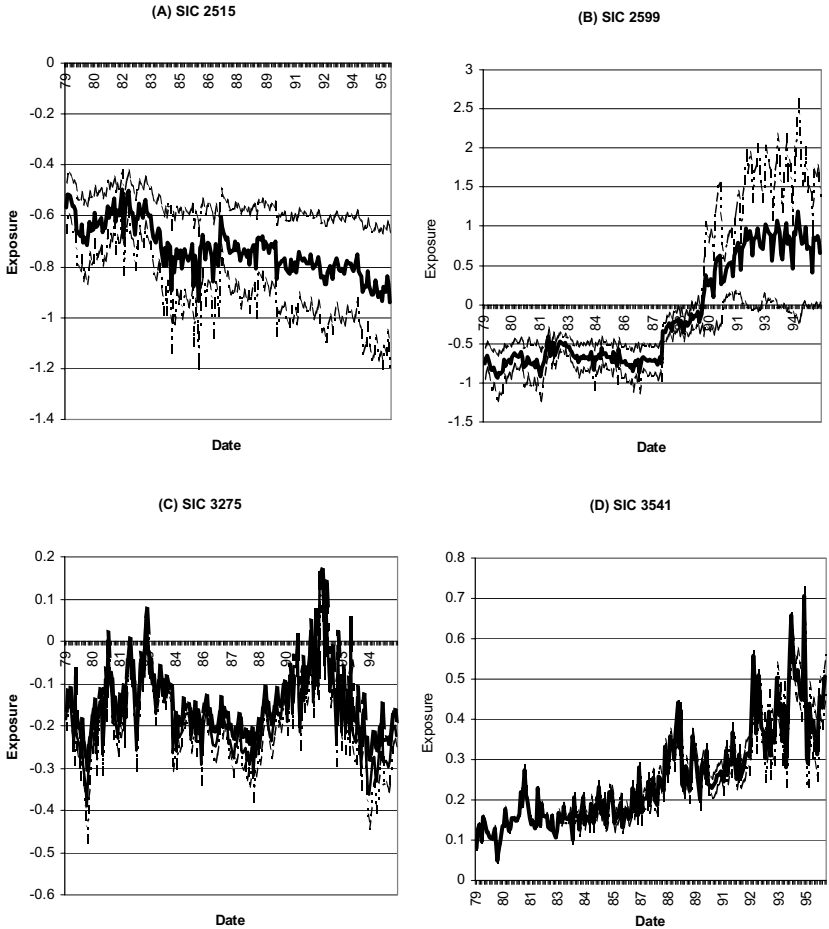


Figure 1
Total exposure and 95% confidence intervals

That is, for the majority of these industries the confidence intervals do not include zero.

To understand the economic meaning and time variation of exposure, consider the mattresses and bedsprings industry (SIC 2515). This industry had a total exposure of -0.566 in January 1979, -0.648 in January 1983, -0.842 in January 1992, and -0.937 in December 1995. This means that a 1% appreciation of the dollar increases the industry return by 0.566% in January 1979, while a similar percentage increase in December 1995 increases its return by 0.937%. As another example, the furnitures and fixtures industry (SIC 2599) has a total exposure that not only varies over time but also switches sign. In January 1979 exposure is -0.750 , by January 1989 it is -0.276 , 0.301 in

January 1991, and 0.660 in December 1995. While a 1% appreciation of the dollar would increase returns by 0.75% in January 1979, a similar percentage appreciation of the dollar would reduce its returns in December 1995 by 0.66%. This is a quite dramatic change of industry exposure over time and is linked to the underlying changes of imported input share, export share, and value of markup.

3.2 The channels of exchange-rate exposure

In this subsection we examine how each of the three channels of exposure contribute to the value of total exposure. Figure 2 graphs the three channels of exposure for a few of the 29 four-digit SIC industries that are significantly affected by exchange-rate movements.³⁰ For a given industry, at each point in time, the sum of the three exposure channels shown in Figure 2 should add to its total exposure graphed in Figure 1. For example, in January 1979, for the furniture and fixtures industry (SIC 2599), exposure through the final good's competitive structure [channel (a)] is 0.014, exposure through export share and final good industry structure [channel (b)] is 0.148, and exposure through imported input share and imported input competitive structure [channel (c)] is -0.916 , and hence the total exposure is -0.750 . In December 1995, exposure through channel (a) is 0.014, 1.638 through channel (b), and -0.992 through channel (c), and hence the total exposure is 0.660. Note that while channel (c) dominates total exposure in January 1979, channel (b) dominates total exposure in December 1995.

In general, we observe different patterns of the three channels of exposure which suggests that the channels of exposure move independently. Channel (a) is smaller in magnitude and relatively less volatile (although it cannot be seen on the graph given its smaller scale). Channels (b) and (c) are larger in magnitude and more volatile. This is expected since channels (b) and (c) include interactions of trade and markup variables. Overall the correlations between each pair of exposure channels are fairly small. In particular, the average correlation between channels (a) and (b) is -0.15 , between channels (a) and (c) is 0.03, and between channels (b) and (c) is -0.048 .

Table 3 presents statistics on the three channels of exposure as well as the total exposure. Specifically, panel A focuses on the industries that are significantly affected by exchange-rate movements and reports the average (across time and across SICs), standard deviation and quartiles of exposure. Note that the average exposure for each channel has the sign predicted by our model [positive for channels (a) and (b) and negative for channel (c)]. The average exposure through the industry structure of the final good [channel (a)] is fairly small (0.018)—even the maximum is only 0.092—and has a standard deviation of 0.002. On average, a 1% appreciation of the dollar decreases industry returns through industry structure by 0.018%. The remaining two

³⁰ See Allayannis and Ihrig (2000) for a complete set of graphs.

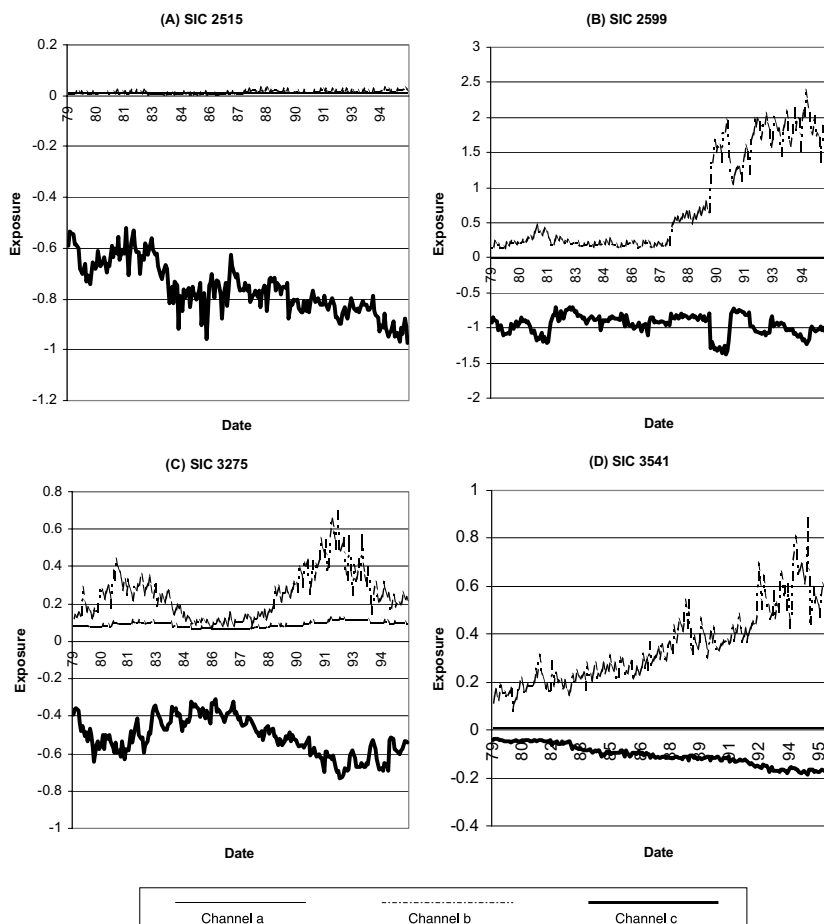


Figure 2
Three channels of exposure

This figure presents our three channels of exposure. Channel (a) captures exposure from the final good's competitive structure. Channel (b) incorporates exposure from the export share and the final goods industry structure. Channel (c) captures exposure from the imported input share and the imported input competitive structure.

channels of exposure play, on average, a larger role (in absolute value) in the value of total exposure than channel (a). In particular, the exposure through the interaction of the final good's industry structure and export share is 0.317, indicating that a 1% appreciation of the dollar decreases industry returns, on average, by 0.317%. Exposure through the interaction of imported input industry structure and imported inputs into production is -0.209 , indicating that a 1% appreciation of the dollar increases industry returns on average by 0.209% through this channel.

The total average exposure for our sample of significantly exposed industries is 0.126, indicating that a 1% appreciation of the dollar reduces industry

Table 3
The size of the exposure

Exposure	Mean	Std. dev.	Min.	Max.	Q_1	Median	Q_3
Panel A. Significantly exposed industries							
$\beta_{2i} \left(\frac{1}{MKUP} \right)$	0.018	0.002	0.005	0.092	0.008	0.009	0.011
$\beta_{2i} \left(\frac{EXP}{V} \right) \left(1 + \frac{1}{MKUP} \right)$	0.317	0.121	0.014	1.503	0.111	0.219	0.349
$\beta_{3i} \left(\frac{1}{IMKUP} \right) \left(\frac{IMP}{V} \right)$	-0.209	0.047	-1.732	0.042	-0.157	-0.004	0.002
Total exposure	0.126	0.107	-0.731	0.598	0.048	0.156	0.254
Panel B. All industries							
$\beta_{2i} \left(\frac{1}{MKUP} \right)$	0.013	0.003	-0.109	0.302	-0.003	0.006	0.015
$\beta_{2i} \left(\frac{EXP}{V} \right) \left(1 + \frac{1}{MKUP} \right)$	0.128	0.102	-0.997	1.503	-0.034	0.037	0.231
$\beta_{3i} \left(\frac{1}{IMKUP} \right) \left(\frac{IMP}{V} \right)$	-0.156	0.067	-1.732	0.887	-0.235	-0.079	0.001
Total exposure	-0.015	0.105	-0.731	0.598	-0.143	0.000	0.156

This table presents statistics (mean, standard deviation, percentiles) of the industry exposure for the three channels of exposure identified by our model defined in Equation (6) for the period 1979:01–1995:12. Panel A reports statistics for the industries that are significantly affected by exchange-rate movements; while panel B reports results for all industries. The average exposure through each channel is calculated as shown in column 1. The total average exposure is the sum of the average exposures of the three channels (i.e., the sum of the previous three rows).

returns by 0.126% on average. This exposure is fairly large, given that it is the average exposure across all significantly exposed industries. The standard deviation of the total exposure is 0.107, while the minimum exposure is -0.731 and the maximum exposure is 0.598. For the industry with the minimum average exposure, a 1% appreciation of the dollar increases its returns by 0.731%. For the industry with the maximum exposure, a 1% appreciation of the dollar reduces its return by 0.598%.

We also present similar results on the channels and total exposure for the entire set of industries in panel B. These results describe the entire distribution of industry exposures through the alternative channels. On average, exposure for each channel has the sign predicted by the model, similar to the case above where only the significantly exposed industries were considered. Exposure through the first channel is also fairly small, and similar to the level of exposure for that channel using only the significant industries. However, the magnitude of the second and third channel of exposure for the entire set of industries is smaller in magnitude than that for the significant industries (0.128 compared with 0.317 and -0.156 compared with -0.209). The resulting total exposure is very small (-0.015) and has a standard deviation of 0.105. Although the average total exposure is small, an industry that only has exports and might therefore be affected through the second channel only, will have a sizable exposure to exchange-rate movements (on average 0.128).

3.3 Exchange-rate exposure and markup volatility

To quantify the increase in precision of including markups in the estimates of exposure, we examine the differences in the estimates of exchange-rate expo-

tures between our model and one of (1) a time-varying trade share (constant markup) model and (2) a model of constant exposure. We expect mismeasurement of exposure by previous models in industries where markups are volatile.³¹ In those industries where markups are relatively stable over time, the mismeasurement of exposure by previous models is relatively small. The small mismeasurement is due to the fact that a stable markup can be captured in the regression coefficient without much error in the estimated exposure. In high-markup time-varying industries, however, assuming constant markups over-, or underestimates exposure, as the actual markup value lies below or above its mean value.

In Figure 3 (A, C) we plot the monthly exposures for a few of the 29 significantly exposed industries estimated under (i) our model of time-varying markup and trade share (time-varying); (ii) under a model of constant markup but time-varying trade (constant markup); and (iii) under a model of constant markup and trade share (constant).³² We calculate exposure by multiplying the estimated regression coefficients by the respective variables for each channel of exposure and then sum up the three exposure components $[\beta_2 * (\frac{1}{MKUP_{it}}) + \beta_2 * (\frac{X_{it}}{V_{it}})(1 + \frac{1}{MKUP_{it}}) + \beta_3 * (\frac{M_{it}}{V_{it}})(\frac{1}{IMKUP_{it}})]$. We also compute and plot the exposure assuming that markups are constant and equal to their average markups by substituting $MKUP_{it}$ and $IMKUP_{it}$ with their average industry markup values over the period 1979–1995. Finally, we estimate exposure when both markups and trade shares are assumed constant to compare our model's estimates to constant exposure estimates. In Figure 3 (B, D), we plot the difference in monthly exposure estimated under models (i) and (ii). The difference reflects the mismeasurement of exposure if one excludes markups. A positive (negative) value of mismeasurement means that a model excluding markups underestimates (overestimates) exposure.

As an example of an industry with a high volatility of markup and a low volatility of trade, consider the gypsum products industry (SIC 3275). When we compare the constant markup exposure to our time-varying exposure, we observe that they differ and that this difference in value also changes over time. For example, in January 1979 (December 1995), the time-varying exposure was -0.185 (-0.226), while the constant markup exposure was -0.170 (-0.302). The difference in the estimated exposure is -0.015 (0.075), or approximately 8.8% (24.8%) of the constant markup exposure. As shown in Figure 3D, assuming markups are constant largely underestimates exposure for the gypsum industry during 1979–1988 and largely overestimates exposure during 1988–1995. On average, for the gypsum industry, the constant markup model misestimates exposure by 32%, while the constant model misestimates exposure by 38% (the exposure under the

³¹ If trade shares are also volatile, then excluding them in the estimate of exposure will also produce misestimation. This point is seen by comparing panel A and panel B of Table 4.

³² See Allayannis and Ihrig (2000) for a complete set of graphs.

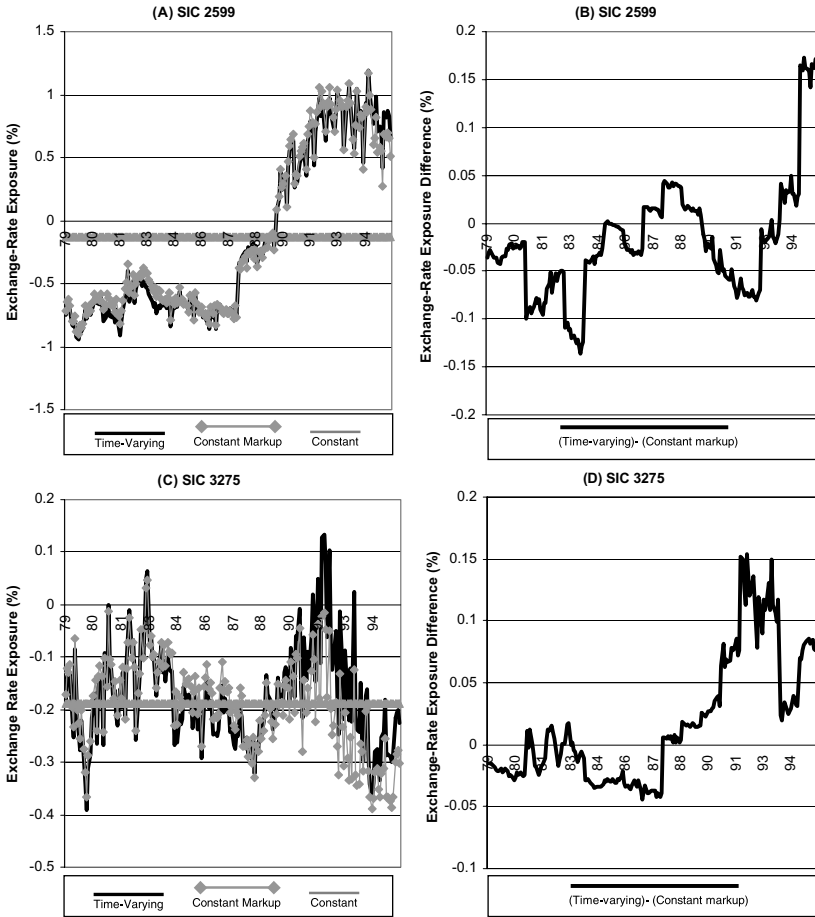


Figure 3
Comparison of exposure across three models

We compare exposure from our model of time-varying markups and trade share, “time-varying,” with two alternatives. First, we compare our model with one that has time-varying trade shares but constant markups, “constant markup.” Second, we compare our model to one where both trade shares and markups are constant, “constant.” There are large obvious deviations between our model’s time-varying exposure and the constant model. Deviations in exposure between our model and the constant markup model are illustrated (B) and (D).

constant model is -0.186). Although these exposure differences can be large in percentage terms, they are not different by orders of magnitude (nor would one expect that from theory). However, a precise estimate of exposure, as the one obtained including markups, can help corporations better hedge their exposures over time.

To study the differences in exposures under the various time-varying trade/markup scenarios, we classify our sample of the 29 significantly exposed U.S. manufacturing industries in four quadrants according to their

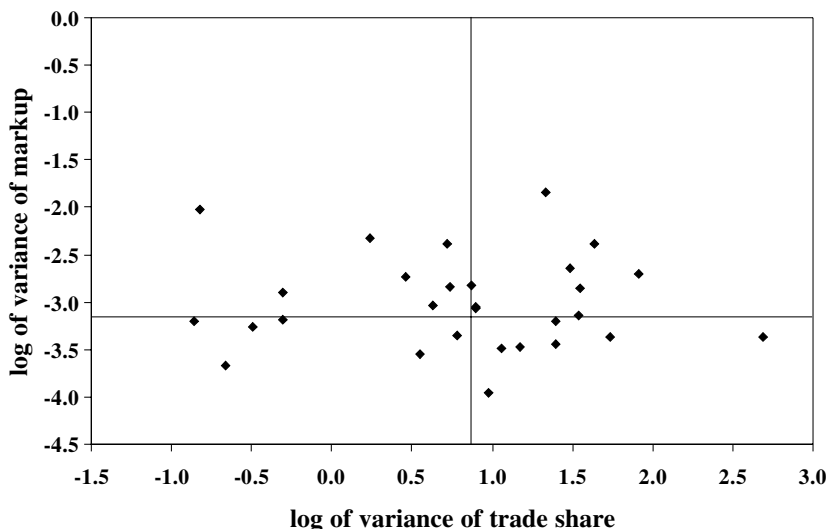


Figure 4
Volatility of markups and trade shares

volatility of markup and trade shares relative to the sample's median values. The trade-share volatility is the equally weighted volatility of imported inputs and exports shares. Markup volatility is an equally weighted volatility of final goods markup and imported input markup. Figure 4 depicts the 29 four-digit SIC industries in the markup/trade volatility space. Low markup-volatility industries are found in the southern section of the plot; while low trade-share-volatility industries are found in the western section of the plot. The quadrants are formed by two lines that are perpendicular to each other and depict the median volatility of trade and the median markup volatility. The median trade volatility is 7.92 (or 0.89 in log) and the median markup volatility is 0.0007 (-3.17 in log).³³ Points in the northeast part of the figure are industries that have above-median volatility of both markup and trade ($H_M H_T$). Points in the northwest section of the figure are industries with above-median markup volatility and below-median trade volatility ($H_M L_T$). Industries in the southwest section of the figure have below-median markup volatility and below-median trade volatility ($L_M L_T$). Finally, industries in the southeast section of the figure have below-median markup volatility and above-median volatility in trade share ($L_M H_T$).

Table 4 presents the average misestimation of the significant industries classified based on their volatility of trade and markup. Panel A compares

³³ Note that the values of markups lie between 0 and 1, whereas trade shares are measured between 1 and 100. If we transform the level of markups to be between 1 and 100, then the median markup volatility is 6.9, which is close to the median trade volatility (7.9).

Table 4
Exposure misestimation

Type	$(1/n)(TV - CM / CM)$	Max.	Min.	$(1/n) TV - CM $	Lower bound
Panel A. Misestimation using a model of constant markup (CM)					
H_M, L_T	12.3%	0.276	-0.191	0.016	4.6%
L_M, L_T	3.0%	0.188	-0.731	0.006	0.8%
L_M, H_T	8.6%	0.577	0.065	0.010	1.8%
H_M, H_T	9.7%	0.346	-0.168	0.017	4.8%
Type	$(1/n)(TV - C / C)$	Max.	Min.	$(1/n) TV - C $	Lower bound
Panel B. Misestimation using a model of constant markup and trade shares (C)					
H_M, L_T	22.0%	0.276	-0.187	0.034	12.2%
L_M, L_T	21.6%	0.188	-0.731	0.038	5.2%
L_M, H_T	38.0%	0.577	-0.130	0.081	14.0%
H_M, H_T	56.4%	0.347	-0.168	0.101	29.1%

This table presents the average exposure misestimation for the sample of industries with significant time-varying exposure that are classified in four quadrants according to the volatility of markup and trade shares. The misestimation of exposures is calculated by comparing the estimate of exposure using our model of time-varying trade share and markup exposure (model TV) with the estimate using a model where markups are considered constant but trade share is time varying (model CM) (panel A) and, with a model where markups and trade shares are held constant (model C) (panel B). Column 1 presents the quadrant an SIC will be classified under, where, for example, H_M, L_T stands for the quadrant that includes industries with high volatility of markup and low volatility of trade. Column 2 presents the average percentage misestimation in exposures (in absolute value). Column 3 presents the maximum average exposure and column 4 presents the minimum average exposure under the constant markup (CM) model (panel A). Column 5 presents the average exposure difference (in absolute value) and column 6 provides a lower bound on the percentage exposure misestimation, which equals the absolute exposure difference (column 5) divided by the absolute value of the maximum exposure (maximum of the absolute value of the maximum or minimum) (columns 3 and 4).

exposure estimates between our model and a constant markup, time-varying trade share model, while panel B compares exposure estimates between our model and the constant model. We expect, and find in the data, that the average misestimation of exposure is larger for industries that have a high volatility of markup and low volatility of trade than for industries with low volatility of markup and low volatility of trade. Row 1 of Table 4 shows the average misestimation, the minimum and maximum exposure over the sample period, and the lower bound of misestimation for the industries that have high volatility of markup and low volatility of trade ($H_M L_T$). Row 2 shows misestimation statistics for industries with low volatility of markups and low volatility of trade ($L_M L_T$). Consistent with our hypothesis, we find that the average misestimation for the former industries is larger than the average misestimation in the latter industries (12.3% versus 3.0%). The lower bound of misestimation is 4.6%. Again, as it can be seen in column 5, the differences in the average level of exposure (as opposed to percentage differences) are small, as expected by theory.

A comparison of panels A and B shows that the average misestimation is larger when comparing our time-varying markup and trade share model to a constant model rather than when comparing our model to a constant markup, but time-varying trade share model. These results provide further evidence that the inclusion of markups leads to more accurate exposure estimates. Even when accounting for the effect of trade shares on exposure, excluding markups produces an average misestimation of 11% [average of $H_M L_T$ (12.3%) and $H_M H_T$ (9.7%)].

4. Conclusions

In this article we investigate how to properly specify and test for factors that affect exchange-rate exposure using a sample of 82 U.S. manufacturing industries at the four-digit SIC level classified in 18 two-digit industry groups between 1979 and 1995. We develop a theoretical model that identifies three channels of exposure: (i) a positive effect through the competitive structure of the markets where final output is sold; (ii) a positive effect through the interaction of the competitive structure of the export market and the share of production that is exported; and (iii) a negative effect through the interaction of the competitive structure of the imported input market and the share of production that is imported. Our model predicts, and we find in the data, that exchange-rate movements have larger effects on an industry's return during low markup periods.

Our estimates suggest that 4 of 18 of the U.S. manufacturing industry groups are significantly affected by exchange-rate movements, a larger number of industry groups than previously thought. On average, a 1% appreciation of the dollar decreases returns by 0.13%. Our model and estimates provide evidence that excluding markups produces less precise estimates of exchange-rate exposure. Even when including trade shares, if markups are volatile, we find previous models have on average misestimated exposure by 11%.

Appendix A

The value function of the firm is given by

$$V(K, e, r) = \max [pq(e, p) + ep^*q^*(e, p^*) - r[K' - (1 - \delta)K] - p_M M(e, p_M) + \rho EV(K', e', r')|e, r]. \tag{A.1}$$

The envelope condition is

$$\frac{\partial V}{\partial e} = p \frac{\partial q}{\partial e} + p^*q^* + ep^* \frac{\partial q^*}{\partial e} - p_M \frac{\partial M}{\partial e} + \rho E \frac{\partial V(K', e', r')}{\partial e'} \frac{de'}{de}. \tag{A.2}$$

This equation solves for V_e . It is a function of the current state variables (K, e, r) . If $E_t K_{t+1} = K_t$, $E_t r_{t+1} = r_t$, and $E_t e_{t+1} = e_t$ (the exchange rate follows a random walk), then by iterative substitution this reduces to

$$\frac{\partial V}{\partial e} = \frac{1}{1 - \rho} \left[p \frac{\partial q}{\partial e} + p^*q^* + ep^* \frac{\partial q^*}{\partial e} - p_M M - p_M \frac{\partial M}{\partial e} \right]. \tag{A.3}$$

Given that $\frac{\partial q}{\partial e} = -\frac{\partial q}{\partial p} \frac{\partial p}{\partial e}$ by definition of the demand function, and $\frac{\partial p}{\partial e} \frac{e}{p} = \frac{\partial p^*}{\partial e} \frac{e}{p^*} + 1$ since we assume domestic and export markups are equal and their costs are the same (i.e., since $MKUP = MKUP^*$ and marginal costs are identical for both final goods outputs, we have $p = ep^*$; taking the derivative of $p = ep^*$ with respect to the exchange rate, we have $\frac{\partial p}{\partial e} =$

$e \frac{\partial p^*}{\partial e} + p^*$; multiplying through by $\frac{e}{p} = \frac{1}{\rho^*}$ obtains our desired result), we simplify the marginal value of the firm with respect to movement in the exchange rate to

$$V_e = \frac{1}{1-\rho} \frac{pq + ep^*q^*}{e} \xi \phi + \frac{1}{1-\rho} \frac{ep^*q^*}{e} [1 + \xi] - \frac{1}{1-\rho} \frac{p_M M}{e} \xi_M \phi_M. \quad (\text{A.4})$$

Appendix B

- 2022—Cheese, natural and processed
- 2033—Canned fruits, vegetables and preserves
- 2043—Cereal breakfast foods
- 2062—Beet and cane sugar
- 2085—Distilled, rectified, and blended liquors
- 2111—Cigarettes
- 2121—Cigars
- 2131—Chewing and smoking tobacco
- 2211—Broad woven fabrics, cotton
- 2221—Manmade fibers
- 2231—Wool
- 2258—Warp knit fabrics
- 2311—Men's and boy's suits and coats
- 2321—Men's and boy's shirts
- 2331—Women's blouses and shirts
- 2337—Women's suits
- 2421—Lumber
- 2435—Hardwood veneer and plywood
- 2436—Softwood veneer
- 2515—Mattresses and bedsprings
- 2599—Furniture and fixtures
- 2711—Newspapers
- 2721—Periodicals
- 2731—Books and pamphlets
- 2752—Printed matter
- 2761—Manifold business forms
- 2782—Blankbooks, looseleaf
- 2812—Alkalies and chlorine
- 2816—Inorganic pigments
- 2819—Industrial inorganic chemicals
- 2821—Plastics, materials and resins
- 2824—Manmade fibers, noncellulosic
- 2833—Medicinals and botanicals
- 2842—Specialty cleaning
- 2865—Cyclic crudes and intermediates
- 2869—Industrial organic chemicals
- 2891—Adhesives and sealants
- 2892—Explosives
- 2893—Printing inks
- 2895—Carbon black
- 2899—Chemical preparations
- 2911—Petroleum refinery products

3143—Men’s footwear
3144—Women’s footwear
3149—Footwear, except rubber
3171—Women’s handbags and purses
3211—Flat glass
3229—Pressed and blown glass
3241—Cement, hydraulic
3275—Gypsum products
3312—Blast furnace, cike oven
3331—Smelter and refined copper
3353—Rolled or drawn aluminum sheet
3423—Hand and edge tools
3429—Hardware
3499—Fabricated metal products
3511—Turbines and turbine generators
3523—Farm machinery
3531—Construction machinery
3537—Industrial trucks and tractors
3561—Pumps and pumping equipment
3567—Industrial furnaces and ovens
3569—Industrial machinery and equipment
3574—Calculating and accounting machines
3585—Air conditioning
3621—Motors and generators and parts
3639—Household appliances
3674—Semiconductors, rectifiers
3675—Electrical capacitors
3711—Motor vehicles and passengers cars
3714—Parts of motor vehicles
3721—Aircraft
3724—Aircraft engines
3728—Aircraft and spacecraft parts
3732—Yachts and pleasure boats
3743—Railway equipment and parts
3751—Motorcycles, bicycles and parts
3842—Orthopedic, prosthetic applications
3861—Photographic equipment
3944—Games and toys
3949—Sporting and athletic goods
3951—Pens, mechanical pencils

Appendix C

To construct intermediate imports and import markups, we need to construct two sets of weights (ω_{kj} s). To create these weights, we first need to create input-output (I-O) tables. The first section describes how the input-output tables were created from the 1987 Benchmark I-O Table Six-Digit Transactions data available from the Bureau of Economic Analysis. The second section describes the creation of the weights.

C.1 Input-Output table

Creating an I-O table for our N industries requires using the “make” and “use” tables from the 1987 Benchmark I-O Accounts of the Bureau of Economic Analysis. The make table is a matrix

showing the industry production of each commodity in the economy at producers prices. The use table is a matrix showing the commodities consumed, or used, by each industry and final consumer at producers' prices.

Using these tables, with matrix dimensions of $N \times m$ and $m \times N$ for the make and use table, respectively, an I-O table, with dimension $N \times N$ is constructed by the following equation:

$$I = use' * \left(\frac{make}{colsum} \right)', \tag{A.5}$$

where I stands for I-O table and $colsum$ stands for the column sum. The equations state that the I-O table equals the cross product of the transpose of the use matrix and the transpose of the make matrix divided by the column sum.

In creating this I-O table we had to deal with differences between the I-O and SIC classification systems. Specifically, there are a few I-O classifications that combine four-digit SICs. For example, the I-O code 34.0201 (shoes except rubber) combines SIC industries 3143–3149. When this arises, the rows and columns for the SIC codes are created using the values from the 340201 I-O code.

The final I-O table, I , is created in three ways, depending on our definition of N . When N is the 82 SIC industries in our sample, I has 82 rows and columns. That is, we ignore the remaining columns and rows that contain industries other than the industries in our sample. When N is the 82 SIC industries in our sample plus all remaining industries, we create an aggregate row and column for the "all remaining industries." Here I has 83 columns and rows. When we set N to be the 82 SICs industries in our sample, other manufacturing and all remaining, we have 84 columns and rows in I . Two columns and rows are for the "other manufacturing" and "all remaining industries."

C.2 Creating weights

For any of the I-O tables, I , two weights are created: column-summed weights (for the M series) and row-summed weights (for the IMKUP series). Creating the column-summed weights requires that each element of a given row be divided by the column sum for that row. This can be illustrated by

	2011	.	.	.	All other
2011	x_{11}	.	.	.	x_{1n}
.	.				.
.	.				.
.
All other	x_{n1}				x_{nn}

where the first element consists of

$$\omega = \frac{x_{11}}{x_{11} + \dots + x_{1n}} \tag{A.6}$$

This is done for each element for a given row where ω_{11} replaces x_{11} , creating a new weight matrix. The row-summed weight matrix can be done in a similar way where each element of a column is divided by the sum for that row. So in this case

$$\omega = \frac{x_{11}}{x_{11} + \dots + x_{1n}}. \tag{A.7}$$

Checking to see if the columns sum to unity for the column-summed weights and if the rows sum to unity for the row-summed weights serves as one method to check for errors.

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