International Review of Economics and Finance xxx (2018) 1–12

Contents lists available at ScienceDirect

International Review of Economics and Finance

journal homepage: www.elsevier.com/locate/iref

The exposure of U.S. manufacturing industries to exchange rates

Willem Thorbecke *

Research Institute of Economy, Trade and Industry and Center for International Development at Harvard, 1-3-1 Kasumigaseki, Chiyoda-ku, Tokyo, 100-8901, Japan

ARTICLE INFO

JEL classification:
F12
F41

Keywords:
Exports
Imports
Elasticities
Exchange rate exposure

ABSTRACT

Safe asset demand and currency manipulation increase the dollar and the U.S. current account deficit. Deficits in manufacturing trade cause dislocation and generate protectionism. Dynamic OLS results indicate that U.S. export elasticities exceed unity for automobiles, toys, wood, aluminum, iron, steel, and other goods. Elasticities for U.S. imports from China are close to one or higher for footwear, radios, sports equipment, lamps, and watches and exceed 0.5 for iron, steel, aluminum, miscellaneous manufacturing, and metal tools. Elasticities for U.S. imports from other countries are large for electrothermal appliances, radios, furniture, lamps, miscellaneous manufacturing, aluminum, automobiles, plastics, and other categories. Stock returns on many of these sectors also fall when the dollar appreciates. Several manufacturing industries are thus exposed to a strong dollar. Policymakers could weaken the dollar and deflect protectionist pressure by promoting the euro, the yen, and the renminbi as alternative reserve currencies.

1. Introduction

The U.S. dollar remains the dominant reserve currency. Demand for the safety of dollar assets such as Treasury securities has strengthened the exchange rate and increased the U.S. current account deficit (see Caballero, Farhi, & Gourinchas, 2015). Currency manipulation may also have raised the dollar's value and worsened the current account (see Bergsten & Gagnon, 2017). While these capital inflows allow Americans to consume more than they produce, the accompanying deficits cause dislocation for U.S. workers and industries.

These difficulties are clear in the case of U.S. manufacturing deficits with China. Autor, Dorn, and Hansen (2013) found that U.S. job losses after China joined the World Trade Organization (WTO) in 2001 occurred in sectors most exposed to competition from China. They also reported that these job losses were not offset by job gains in other sectors. Acemoglu, Autor, Dorn, Hanson, and Price (2014) noted that the loss of U.S. manufacturing jobs over this period was "stunning," equal to 33 percent of U.S. manufacturing jobs. They found that competition from China's imports caused more than 2.4 million job losses between 1999 and 2011. Pierce and Schott (2016) showed that the largest drops in U.S. manufacturing employment and the largest increases in imports were in goods for which China obtained the greatest tariff reductions when it joined the WTO.

Many other countries such as Germany, Japan, South Korea, and Switzerland also run large current account surpluses and large surpluses in manufacturing trade with the U.S. Fig. 1 presents the U.S. manufacturing deficits with China and with all other counties. It shows that the U.S. deficits with both China and with other countries exceed 2 percent of GDP. The figure also shows that since the 2008–2009 Global Financial Crisis the surpluses with China and with all other countries have converged. These surpluses generate protectionist pressures, as seen by the election of President Donald Trump on a protectionist platform.

* Corresponding author.
E-mail address: willem-thorbecke@rieti.go.jp.

https://doi.org/10.1016/j.iref.2018.06.002
Received 5 December 2017; Received in revised form 11 May 2018; Accepted 5 June 2018
Available online xxxx
1059-0560/

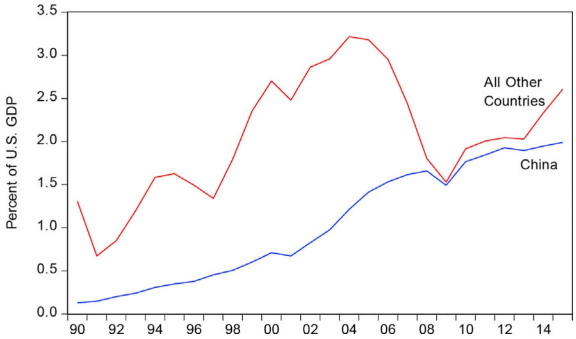

Fig. 1. The U.S. deficit in manufacturing trade with China and other countries.
Source: The CEPII-CHELEM database.

This paper investigates what sectors in the U.S. are most exposed to exchange rates. To do this it employs cointegration analysis to investigate long run trade elasticities for manufacturing exports and imports in individual sectors. It also estimates exchange rate elasticities for imports from China and from other countries separately.

In previous work, Chinn (2010) used dynamic ordinary least squares (DOLS) techniques to estimate trade elasticities for U.S. exports and imports over the 1975Q1-2010Q1 period. In his baseline specification, he found an exchange rate elasticity of 0.6 and an income elasticity of 1.9 for goods exports excluding agriculture (GEEXAG). For goods imports excluding oil (GIEXOIL) he found an exchange rate elasticity of −0.45 and an income elasticity of 2.6. Thus he noted that the Houthakker-Magee effects (i.e., the finding that income elasticities for U.S. imports substantially exceed income elasticities for U.S. exports) remain present in the estimates. To control for supply side factors, he included U.S. manufacturing production in export functions and import-weighted rest-of-world GDP in import functions. For GEEXAG the exchange rate elasticities in this specification exceeded unity and the income elasticities became insignificant. For GIEXOIL the exchange rate elasticities now equaled −0.5 and the income elasticities exceeded 2.2. Finally, Chinn included the average tariff rate for major economies and the relative price of oil to proxy for trade costs. For GEEXAG the price elasticity now equaled 0.75 and the income elasticity 0.9 and for GIEXOIL the corresponding elasticities were −0.43 and 0.9. Chinn noted that disaggregating trade flows attenuates aggregation bias and improves price elasticity estimates.

Arize (2017) used autoregressive distributed lag techniques to investigate the relationship between the U.S. trade balance, the real effective exchange rate, and U.S. GDP over the 1980Q1 to 2015Q3 period. He reported that a 1 percent depreciation of the dollar would improve the trade deficit in the long run by 1.3 percent. He concluded that a dollar depreciation would significantly improve but not eliminate the U.S. trade deficit.

Cheung, Chinn, and Qian (2015) examined U.S. imports from China over the 1994Q1 to 2012Q4 period. They employed the Pesaran, Shin, and Smith (2001) bounds testing approach that allows variables to have different orders of integration. For the CPI-deflated real exchange rate, they found that a 10 percent depreciation of the renminbi would raise U.S. imports from China by 17 percent. They also found income elasticities of greater than 3.

This paper presents disaggregated estimates of trade elasticities. Orcutt (1950) noted that estimating trade elasticities using disaggregated data reduces aggregation bias when elasticities differ by industry. The results in this paper indicate that U.S. exports of automobiles, toys, wood, aluminum, iron & steel, and several other goods tend to fall by more than one percent when the dollar appreciates by one percent. On the other hand, exports of sophisticated products such as pharmaceuticals and organic chemicals are not affected by exchange rates. On the import side, the findings are clearer when imports from China and other countries are investigated separately. For imports from China, exchange rate elasticities are close to unity or higher for footwear, radios, sports equipment, lamps, and watches. They are also greater than 0.5 for iron & steel, aluminum, miscellaneous manufacturing articles, and base metal tools. For imports from countries other than China, price elasticities are close to unity or higher for electrothermal appliances (e.g., water & space heaters), radios, furniture, lamps, and miscellaneous manufacturing articles. They are greater than 0.5 for aluminum, motor vehicles, and plastic articles. In addition, they are positive and statistically significant for several other categories and insignificant for pharmaceuticals.

To investigate how exchange rates affect manufacturing sectors, this paper also examines the stock market response of various industries to changes in the dollar. Theory posits that stock prices equal the expected present value of future net cash flows. Investigating how exchange rates affect sectoral stock returns can thus shed light on how industry profitability is affected.

Many studies have found little evidence that exchange rates affect U.S. stock returns (see Bartram & Bodnar, 2007, and the literature summarized there). Bartram, Brown, and Minton (2010) referred to this lack of evidence as the “exposure puzzle” and reported that operational and financial hedging and the pass-through of exchange rates into consumer prices reduce the effects of exchange rate changes on stock returns.

This paper, employing more recent data than Bartram and Bodnar (2007) including the period after 2000 when U.S. manufacturing employment tumbled, finds that many of the same industries that export less and face greater import competition when the dollar appreciates also experience larger drops in stock prices. These include aluminum, forestry, paper, motor vehicles, footwear, iron, and steel. Other sectors with low elasticities of exports and imports such as pharmaceuticals and medical equipment also have low stock market exposures to exchange rates. Some sectors that purchase imported goods and sell them to U.S. consumers such as consumer discretionary goods and apparel benefit from a stronger dollar.

These results perhaps point to a "hollowing-out" effect from a strong dollar. If demand for safe assets or currency manipulation keep the dollar stronger than it would otherwise be, sectors such as motor vehicles, metals, forestry, paper, and footwear face large increases in imports and large drops in exports and stock prices. U.S. sectors that import goods produced abroad to sell to U.S. consumers benefit. The export and import-competing sectors that are harmed will tend to contract and the importing sectors that are profitable will tend to expand, hollowing out the U.S. manufacturing sector.

The next section investigates the exchange rate elasticities for manufacturing industries. Section III examines the stock market response to news of exchange rates. Section IV concludes.

2. Investigating trade elasticities for manufactured goods

2.1. Data and methodology

To estimate import and export elasticities the imperfect substitutes model is employed. As Chinn (2010) noted, this model is well suited for manufacturing goods. In this framework imports and exports are functions of the real exchange rate and of real GDP in the importing countries.

The U.S. International Trade Commission provides data on U.S. imports and exports disaggregated to the 2-digit and 4-digit Harmonized System (HS) level. The U.S. Bureau of Labor Statistics (BLS) provides import and export price data for selected 2-digit and 4-digit HS categories. The volume of imports or exports in each category is calculated as the dollar value of imports or exports divided by the import or export price in the corresponding category.

The imperfect substitutes model posits that trade volumes depend on the real exchange rate and real GDP in the importing countries. The real exchange rate employed is the Federal Reserve real broad effective exchange rate. This exchange rate is CPI-deflated. Since much U.S. trade is with emerging economies, the broad measure is preferable to the Federal Reserve real effective exchange rate with major currencies. When examining imports from China, the real CPI-deflated renminbi/dollar exchange rate is employed. U.S. real GDP is used for U.S. imports and a geometric average of real GDP in nine leading trading partners is used for U.S. exports. Data on the exchange rate, the CPI, and U.S. GDP come from the Federal Reserve Bank of St. Louis FRED database and data on trading partners' real GDP come from the OECD.

The goal in this paper is to obtain good estimates where possible rather than a large number of questionable estimates. Mead (2014) has shown that trade prices that the BLS collects from companies are superior to producer price indices or unit values for deflating trade statistics. This paper thus examines those HS 2- and 4-digit categories of manufacturing imports and exports for which the BLS provides import and export price data.[1] It tests whether these series and the real exchange rate and real GDP are integrated of order one using augmented Dickey-Fuller tests. It also uses the trace statistic and the maximum eigenvalue statistic to test the null hypothesis of no cointegrating relations between exports or imports and the real exchange rate and real GDP against the alternative hypothesis of one cointegrating relation. It employs the Akaike Information Criterion and the Schwarz Criterion to test for the number of lags in the unconstrained vector autoregression and for the presence of trends in the data and the cointegrating vector.[2] This paper then uses the HS categories of exports or imports that exhibit cointegrating relations with the real exchange rate and real income.[3]

The cointegrating equations are estimated using DOLS. DOLS yields consistent and efficient estimates (Stock & Watson, 1993). The DOLS estimator also has smaller bias and root mean squared error than other estimators of cointegrating vectors in cases where the sample is not large enough to justify applying asymptotic theory (Montalvo, 1995). For exports, DOLS estimates of the long run parameters α_1, α_2, and α_3 can be obtained from the following regression:

$$ex_t = \alpha_1 + \alpha_2 reer_t + \alpha_3 y_t{}^* + \sum_{k=-K}^{K} \beta_{1,k} \Delta reer_{t+k} + \sum_{k=-K}^{K} \beta_{2,k} \Delta y_{t+k}{}^* + \varepsilon_t, \tag{1}$$

where ex represents exports, reer represents the real effective exchange rate, y* represents income in the importing countries and K represents the number of leads and lags of the first differenced variables. For imports, the corresponding equation is:

$$im_t = \alpha_4 + \alpha_5 reer_t + \alpha_6 y_t + \sum_{k=-K}^{K} \beta_{3,k} \Delta reer_{t+k} + \sum_{k=-K}^{K} \beta_{4,k} \Delta y_{t+k} + u_t, \tag{2}$$

where im represents imports, reer represents the real renminbi/dollar exchange rate in the case of imports from China and the real effective exchange rate otherwise, y represents U.S. income, and the other variables are defined after equation (1). Four lags and two leads of the first differenced variables are employed.

[1] Trade in parts and similar inputs are not considered since much of this trade flows back and forth between the U.S., Canada, and Mexico. Following previous research, fuel imports are also excluded (see Gruber, McCallum, & Vigfusson, 2016). Finally, imports of computers, semiconductors, and phones are excluded because these are produced within long supply chains with value added coming from many countries (see Thorbecke, 2017).

[2] When the model selection criteria point to a trend in the cointegrating vector, a trend term is included when estimating trade elasticities.

[3] Some sectors may be excluded from the estimation, not because the exchange rate does not matter, but because there is not a long enough time series of export or import prices to test for cointegration.

Table 1
Dynamic OLS estimates for U.S. manufacturing exports to all countries.

Sector (HS Code)	Exchange Rate Coefficient (HAC S.E.)	Real GDP Coefficient (HAC S.E.)	Product Complexity Ranking	Adjusted R-squared	Standard Error of Regression
Animal Feed (23)	−2.51*** (0.31)	2.10*** (0.13)	780	0.899	0.152
Motor Vehicles (8703)	−1.86*** (0.22)	2.34*** (0.11)	194	0.942	0.110
Phones (8517)	−1.73** (0.72)	4.62*** (0.16)	293	0.958	0.159
Toys (95)	−1.64*** (0.24)	1.50*** (0.12)	459	0.899	0.107
Petroleum Oils[a] (excluding Crude Oil) (2710)	−1.61*** (0.21)	0.49** (0.19)	1021	0.974	0.103
Wood & Pulp (47)	−1.27*** (0.07)	0.57*** (0.04)	639	0.918	0.047
Iron & Steel (72)	−1.19*** (0.26)	3.52*** (0.98)	603	0.939	0.097
Aluminum (76)	−1.12** (0.13)	1.76*** (0.09)	597	0.947	0.072
Instruments for Scientific Analysis (9027)	−1.06*** (0.13)	2.58*** (0.07)	33	0.985	0.053
Taps & Valves (8481)	−0.84*** (0.17)	2.57** (0.65)	80	0.985	0.048
Soap, Wax (34)	−0.75*** (0.10)	1.49*** (0.38)	527	0.964	0.035
Paper (48)	−0.63*** (0.16)	1.21*** (0.12)	423	0.910	0.065
Glassware (70)	−0.19* (0.11)	1.76*** (0.05)	362	0.968	0.049
Copper (74)	−0.19 (0.24)	1.66*** (0.11)	761	0.831	0.113
Misc. Chemicals (38)	−0.16* (0.09)	1.77*** (0.07)	250	0.977	0.044
Pharmaceuticals (30)	−0.04 (0.21)	4.39*** (0.10)	234	0.985	0.167
Plastics (39)	0.08 (0.11)	1.93*** (0.07)	387	0.976	0.046
Organic Chemicals (29)	0.23* (0.13)	1.26*** (0.09)	282	0.888	0.066
Metal Articles (83)	0.48*** (0.08)	0.63*** (0.04)	355	0.891	0.038
Computers (8471)	0.49** (0.20)	5.03** (1.16)	361	0.959	0.094

Notes: The table reports dynamic OLS estimates of trade elasticities for quarterly U.S. manufacturing exports to all countries. The dependent variable is the value of exports in the Harmonized System (HS) category deflated using export prices for the same HS category. These data are obtained from the U.S. International Trade Commission and the U.S. Bureau of Labor Statistics. The real exchange rate is the Federal Reserve real broad effective exchange rate. These data are obtained from the Federal Reserve Bank of St. Louis FRED database. GDP is trade-weighted real GDP in nine major importing countries. These data are calculated using data from the OECD and the CEPII-CHELEM database. Product Complexity Ranking is the average ranking of the product category over the 1995–2015 period using the measures of Hausmann et al. (2014). HAC S.E. are heteroscedasticity and autocorrelation consistent standard errors. Seasonal dummies are included and in some cases dummy variables for the Global Financial Crisis are included. The regressions include four lags and two leads of the first differenced right hand side variables. The original data extend from 1992Q4 to 2017Q1. After taking lags, the regressions have 91 observations.
*** (**) [*] denotes significance at the 1% (5%) [10%] levels.
[a] The unit root tests, cointegration tests, and estimation take account of a structural break (see Johansen, Mosconi, & Nielsen, 2000; Perron, 1989; Perron & Vogelsang, 1993).

The data extend from either 1992Q4 or 1993Q1 to either 2017Q1 or 2017Q2.[4] For many import categories and for a few export categories, there are temporary drops associated with the Global Financial Crisis. These are controlled for using dummy variables. Seasonal dummies are also included.

2.2. Results

Table 1 presents the results for exports. Fourteen of the twenty categories have exchange rate elasticities that are negative and statistically significant at at least the 10 percent level. Nine of these categories have elasticities exceeding unity in absolute value.

Motor vehicle exports have an exchange rate elasticity of −1.86, indicating that a 10 percent appreciation of the dollar will reduce the volume of exports by almost 19 percent. Automobile exports are thus very exposed to the value of the dollar. Aluminum and iron & steel exports also have elasticities greater than unity. Forestry exports are sensitive to the exchange rate, with the elasticity for wood & pulp exports equal to −1.27 and the elasticity for paper exports equal to −0.63. On the other hand, there is no evidence that pharmaceuticals, chemicals, and plastics exports are affected by exchange rates.

Table 2 presents the results for imports. Motor vehicles and aluminum imports are sensitive to the dollar, with elasticities of 0.60 and 0.47 respectively. Pharmaceutical imports are not sensitive to exchange rates.

Table 2 does not provide strong evidence that imports in general are sensitive to exchange rates. Twelve of the categories have exchange rate elasticities that are of the expected positive sign and statistically significant at at least the 10 percent level and nine of the categories have elasticities that are negative and statistically significant at at least the 10 percent level. This may reflect Chinn (2010) observation that it is difficult to model U.S. imports.

Table 3 examines imports from China. Eleven of the categories have exchange rate elasticities that are of the expected positive sign and statistically significant at at least the 10 percent level and only four of the categories have elasticities that are negative and statistically significant at at least the 10 percent level. Imports of footwear and toys & sports equipment are sensitive to exchange rates, with elasticities of 1.50 and 0.91. Radios, lamps, and watches & clocks all have elasticities close to unity. Iron & steel imports and aluminum imports have elasticities of 0.79 and 0.63, although in the case of iron & steel the coefficient is not statistically significant. Miscellaneous

[4] To obtain long enough time series to perform cointegration analysis, those HS categories that have trade prices available beginning in 1992 are employed. This provides about 100 observations in the unconstrained vector autoregression.

Table 2
Dynamic OLS estimates for U.S. manufacturing imports from all countries.

Sector (HS Code)	Exchange Rate Coefficient (HAC S.E.)	Real GDP Coefficient (HAC S.E.)	Product Complexity Ranking	Adjusted R-squared	Standard Error of Regression
Lamps (9405)	0.95*** (0.14)	3.27*** (0.06)	277	0.978	0.073
Furniture, Bedding (94)	0.91*** (0.08)	3.32*** (0.04)	605	0.994	0.039
Radios (8527)	0.79** (0.35)	0.94 (0.64)	611	0.745	0.107
Motor Vehicles (8703)	0.60*** (0.12)	1.65*** (0.06)	194	0.945	0.063
Footwear (6403)	0.52*** (0.13)	0.70*** (0.11)	1016	0.985	0.052
Toys & Sports Equip. (95)	0.48** (0.21)	1.77*** (0.16)	603	0.929	0.108
Aluminum (76)	0.47*** (0.21)	1.57*** (0.11)	730	0.869	0.091
Ceramic Products (69)	0.35* (0.17)	2.85*** (0.47)	778	0.912	0.058
Clothing (61)	0.33*** (0.11)	2.45*** (0.11)	1158	0.973	0.066
Electrothermal Appliances (8516)	0.32** (0.15)	2.67** (0.08)	446	0.976	0.071
Misc. Manufactured Articles (96)	0.28*** (0.07)	1.83*** (0.05)	581	0.981	0.038
Glass & Glassware (70)	0.24** (0.10)	2.34*** (0.24)	441	0.974	0.035
Pharmaceuticals (30)	0.14 (0.26)	5.76*** (0.19)	244	0.982	0.126
Base Metal Articles (83)	0.04 (0.14)	3.01*** (0.23)	383	0.986	0.041
Electrical Transformers (8504)	−0.02 (0.29)	2.56*** (0.23)	458	0.909	0.123
Diamonds (7102)	−0.02 (0.19)	3.18*** (0.39)	1038	0.962	0.083
Electric Motors (8501)	−0.04 (0.14)	2.33*** (0.09)	386	0.970	0.063
Base Metal Articles (83)	−0.05 (0.11)	3.19*** (0.20)	383	0.991	0.032
Clocks & Watches (91)	−0.20 (0.20)	1.98*** (0.42)	715	0.890	0.068
Leather Articles (42)	−0.21** (0.11)	1.48** (0.06)	991	0.943	0.065
Optical, Photographic & Medical Instruments (90)	−0.23** (0.08)	2.19*** (0.22)	196	0.995	0.032
Air & Vacuum Pumps (8414)	−0.26* (0.14)	2.32*** (0.10)	143	0.958	0.073
Plastic Articles (3926)	−0.27*** (0.09)	2.48*** (0.07)	234	0.985	0.047
Rubber (40)	−0.35*** (0.08)	2.38*** (0.05)	536	0.988	0.038
Worn Textile Articles (63)	−0.43* (0.21)	5.40*** (0.53)	1075	0.989	0.067
Beverages & Spirits (22)	−0.52*** (0.18)	3.49*** (0.36)	871	0.984	0.054
Iron & Steel (72)	−0.52 (0.47)	2.00* (1.01)	597	0.621	0.135
Taps & Valves (8481)	−0.77*** (0.19)	4.62*** (0.43)	80	0.975	0.050
Pumps for Liquids (8413)	−1.19*** (0.15)	2.19*** (0.40)	90	0.990	0.052

Notes: The table reports dynamic OLS estimates of trade elasticities for quarterly U.S. manufacturing imports from all countries. The dependent variable is the value of imports in the Harmonized System (HS) category deflated using import prices for the same HS category. These data are obtained from the U.S. International Trade Commission and the U.S. Bureau of Labor Statistics. The real exchange rate is the Federal Reserve real broad effective exchange rate and GDP is real U.S. GDP. These data are obtained from the Federal Reserve Bank of St. Louis FRED database. Product Complexity Ranking is the average ranking of the product category over the 1995–2015 period using the measures of Hausmann et al. (2014). HAC S.E. are heteroscedasticity and autocorrelation consistent standard errors. Seasonal dummies are included and in some cases dummy variables for the Global Financial Crisis are included. The regressions include four lags and two leads of the first differenced right hand side variables. The original data extend from 1992Q4 to 2017Q2. After taking lags, the regressions have 92 observations.
*** (**) [*] denotes significance at the 1% (5%) [10%] levels.

manufactured articles have an import elasticity of 0.63.

Table 4 examines imports from all countries other than China. Thirteen of the categories have exchange rate elasticities that are of the expected positive sign and statistically significant at at least the 10 percent level and only two of the categories have elasticities that are negative and statistically significant at at least the 10 percent level. Electrothermal appliances, radios, and furniture & bedding have elasticities above one. Lamps and miscellaneous manufactures have elasticities close to unity. Aluminum imports have an elasticity of 0.71 and motor vehicle imports have an elasticity of 0.60. Pharmaceutical products have an exchange rate elasticity that is small and not statistically significant.

Calculating a weighted average of the export elasticities in Table 1, with the weights based on the value of exports in each category relative to the value of exports in all the categories in the table, the overall export elasticity equals −0.81. Performing the same calculation for imports in Tables 3 and 4, the import elasticity equals 0.34. The sum of the export and import elasticities thus exceed one, implying that the Marshall-Lerner condition holds. Thus, for the goods studied here, a depreciation of the dollar should improve the trade balance.

Paralleling Chinn's (2010) findings, the income elasticities for imports from the world in Table 2 are high. Paralleling Cheung, Chinn, and Qian's (2015) findings, the income elasticities for imports from China in Table 3 are even higher. The income elasticities for imports from the world excluding China in Table 4 are smaller than those in Tables 2 and 3 Comparing overlapping HS categories across the three tables, the average income elasticities are 2.48 for imports from the world, 4.13 for imports from China, and 1.75 for imports from other countries. The income elasticities for China may be artificially inflated because U.S. GDP and U.S. imports from China have both increased rapidly over the sample period.[5] If this is true, one reason the Houthakker-Magee asymmetry remains so prominent in recent work estimating U.S. trade elasticities is an artifact of the increasing share of Chinese goods in U.S. imports.

Unlike the case of watch and clock imports from China, watch and clock imports from other countries are not sensitive to exchange

[5] This should not affect estimates of the exchange rate elasticity, since the renminbi/dollar real exchange rate has experienced several increases and decreases over the sample period.

Table 3
Dynamic OLS estimates for U.S. manufacturing imports from China.

Sector (HS Code)	Exchange Rate Coefficient (HAC S.E.)	Real GDP Coefficient (HAC S.E.)	Product Complexity Ranking	Adjusted R-squared	Standard Error of Regression
Footwear (6403)	1.50*** (0.17)	2.23*** (0.22)	1016	0.809	0.140
Radios (8527)	0.97*** (0.32)	1.63*** (0.23)	611	0.630	0.196
Toys, Sports Equip. (95)	0.91*** (0.16)	3.34*** (0.23)	712	0.944	0.133
Lamps (9405)	0.88*** (0.15)	4.18*** (0.12)	277	0.963	0.114
Watches & Clocks (91)	0.86*** (0.18)	1.67*** (0.14)	641	0.839	0.116
Iron & Steel (72)	0.79 (0.78)	4.86*** (0.66)	579	0.737	0.389
Misc. Manufacturing Articles (96)	0.63*** (0.09)	4.55*** (0.12)	699	0.984	0.081
Aluminum (76)	0.63** (0.31)	8.76*** (0.32)	538	0.977	0.195
Base Metal Tools (82)	0.54*** (0.14)	4.96*** (0.12)	403	0.986	0.085
Glass & Glassware (70)	0.44*** (0.15)	6.52** (0.13)	415	0.988	0.106
Paper (48)	0.37** (0.16)	5.93*** (0.18)	634	0.986	0.106
Electrothermal Appliances (8516)	0.33* (0.17)	4.96*** (0.16)	446	0.980	0.117
Toys (9503)	0.15 (0.16)	2.15*** (0.19)	934	0.939	0.112
Ceramics (69)	0.14 (0.15)	2.67*** (0.19)	853	0.580	0.142
Electrical Transformers (8504)	0.02 (0.22)	5.15*** (0.30)	458	0.954	0.173
Plastics (39)	−0.12 (0.09)	4.14*** (0.09)	486	0.992	0.057
Electric Circuit Switching (8536)	−0.16 (0.13)	4.24** (0.14)	362	0.979	0.098
Air & Vacuum Pumps (8414)	−0.18 (0.16)	4.39*** (0.14)	143	0.947	0.178
Plastic, Polymer, and Resin Articles (3926)	−0.51*** (0.12)	3.28*** (0.13)	234	0.980	0.077
Electrical Motors (8501)	−0.91*** (0.15)	4.70*** (0.16)	386	0.981	0.103
Optical, Photographic, & Medical Instruments (90)	−1.10*** (0.09)	4.17*** (0.10)	>285	0.991	0.070
Organic Chemicals (29)	−1.74*** (0.25)	5.15*** (0.27)	223	0.982	0.130

Notes: The table reports dynamic OLS estimates of trade elasticities for quarterly U.S. manufacturing imports from China. The dependent variable is the value of imports in the Harmonized System (HS) category deflated using import prices for the same HS category. These data are obtained from the U.S. International Trade Commission and the U.S. Bureau of Labor Statistics. The real exchange rate is the real CPI-deflated renminbi-dollar exchange rate, calculated using data from the Federal Reserve Bank of St. Louis FRED database. GDP is real U.S. GDP. Product Complexity Ranking is the average ranking of the product category over the 1995–2015 period using the measures of Hausmann et al. (2014). HAC S.E. are heteroscedasticity and autocorrelation consistent standard errors. Seasonal dummies are included and in some cases dummy variables for the Global Financial Crisis are included. The regressions include four lags and two leads of the first differenced right hand side variables. The original data extend from 1993Q1 to 2017Q2. After taking lags, the regressions have 91 observations.
***(**) [*] denotes significance at the 1% (5%) [10%] levels.

rates. This may reflect the observation of Petri and Plummer (2009) that China often produces at lower price points within individual product categories. While countries such as Switzerland sell high-end watches and clocks to the U.S., China often sells lower-end products. More sophisticated products may be valued more by buyers, making them less sensitive to price fluctuations in their buying decisions. If so, this means that producers of more technologically advanced products have greater market power (Arbatli & Hong, 2016).

To test for the relationship between product sophistication and price elasticities the measures of Hidalgo and Hausmann (2009) are used. Hidalgo and Hausmann employed the method of reflections to measure the complexities of economies and products. For an economy, they measured complexity by its diversification. They defined diversification as the number of products that a country exports with revealed comparative advantage (RCA) greater than one. For a product, they measured complexity by its ubiquity. They defined ubiquity as the number of countries that export the product with RCA greater than one. Intuitively, an economy that exports more products with RCA greater than one is more diversified and a product that fewer countries export with RCA greater than one is less ubiquitous. Higher diversification implies that an economy has more capabilities and lower ubiquity implies that the product requires more capabilities to produce.

Hausmann et al. (2014) used this approach to rank the sophistication of 1239 products disaggregated at the HS 4-digit level for every year between 1995 and 2015. To test for a relationship between product complexity and price elasticities, the elasticities reported in Tables 1 through 4 are regressed on the average ranking of the corresponding HS category over the 1995–2015 period. When Tables 1 through 4 contain 2-digit HS categories, a weighted average product ranking is calculated using rankings for each 4-digit product category weighted by the share of exports or imports in each of the 4-digit product categories that comprise the 2-digit category. The same 2-digit HS category can thus have different values in Tables 1 through 4 because the shares of exports or imports in the 4-digit categories differ across the four tables.

Fig. 2 through Fig. 5 presents scatter plots of average product rankings versus price elasticities together with regression results. For U.S. exports and especially for U.S. imports from China, greater product sophistication is associated with lower price elasticities. For U.S. imports from the world and from the world excluding China, on the other hand, there does not appear to be a close relationship between these two variables.

The important implication of the results in this section is that U.S. exports and imports in several manufacturing categories are sensitive to exchange rates. This is especially true of automobiles, metals, forestry products, and footwear. On the other hand, trade in pharmaceutical products, rubber, and chemicals are insensitive to exchange rates. For U.S. exports and especially for U.S. imports from China, trade in more sophisticated products appears to be less sensitive to exchange rates.

Table 4
Dynamic OLS Estimates for U.S. manufacturing Imports from Countries other than China.

Sector (HS Code)	Exchange Rate Coefficient (HAC S.E.)	Real GDP Coefficient (HAC S.E.)	Product Complexity Ranking	Adjusted R-squared	Standard Error of Regression
Electrothermal Appliances (8516)	1.51*** (0.12)	0.82*** (0.08)	446	0.894	0.062
Radios (8527)	1.35*** (0.29)	−0.15 (0.23)	611	0.754	0.140
Furniture, Bedding (94)	1.16*** (0.10)	2.19*** (0.04)	594	0.963	0.042
Lamps (9405)	0.95*** (0.22)	1.55*** (0.62)	277	0.959	0.070
Misc. Manufactured Articles (96)	0.82*** (0.27)	0.42*** (0.13)	563	0.583	0.130
Aluminum (76)	0.71*** (0.21)	1.23*** (0.10)	750	0.809	0.091
Motor Vehicles (8703)	0.60*** (0.12)	1.64*** (0.06)	194	0.945	0.063
Plastic, Polymer, & Resin Articles (3926)	0.58*** (0.21)	1.20*** (0.34)	234	0.975	0.044
Electric Motors (8501)	0.43** (0.21)	1.61*** (0.39)	386	0.954	0.065
Base Metal Articles (83)	0.34** (0.12)	2.50*** (0.25)	354	0.963	0.041
Vegetable, Fruit, & Nut Preparations (20)	0.31** (0.13)	1.67*** (0.11)	897	0.937	0.067
Base Metal Tools (82)	0.29*** (0.10)	1.25*** (0.05)	225	0.900	0.059
Sports Equip. (9506)	0.25** (0.12)	−0.16 (0.10)	613	0.603	0.078
Pharmaceuticals (30)	0.17 (0.26)	5.76*** (0.19)	247	0.982	0.127
Iron & Steel (72)	0.16 (0.26)	0.26** (0.12)	600	0.632	0.132
Plastics (39)	0.02 (0.10)	3.24*** (0.27)	422	0.967	0.032
Taps & Valves (8481)	−0.04 (0.15)	2.53** (0.08)	80	0.977	0.056
Rubber (40)	−0.09 (0.08)	2.01*** (0.04)	578	0.981	0.041
Clocks & Watches (91)	−0.07 (0.12)	0.85*** (0.05)	674	0.842	0.079
Air & Vacuum Pumps (8414)	−0.13 (0.11)	1.81*** (0.09)	143	0.944	0.066
Toys (9503)	−0.53** (0.22)	0.47*** (0.15)	934	0.740	0.125
Pumps (8413)	−0.85*** (0.34)	1.87*** (0.34)	90	0.987	0.048

Notes: The table reports dynamic OLS estimates of trade elasticities for quarterly U.S. manufacturing imports from all countries other than China. The dependent variable is the value of imports in the Harmonized System (HS) category deflated using import prices for the same HS category. These data are obtained from the U.S. International Trade Commission and the U.S. Bureau of Labor Statistics. The real exchange rate is the Federal Reserve real broad effective exchange rate and GDP is real U.S. GDP. These data are obtained from the Federal Reserve Bank of St. Louis FRED database. GDP is real U.S. GDP. Product Complexity Ranking is the average ranking of the product category over the 1995–2015 period using the measures of Hausmann et al. (2014). HAC S.E. are heteroscedasticity and autocorrelation consistent standard errors. Seasonal dummies are included and in some cases dummy variables for the Global Financial Crisis are included. The regressions include four lags and two leads of the first differenced right hand side variables. The original data extend from 1992Q4 to 2017Q2. After taking lags, the regressions have 92 observations.
*** (**) [*] denotes significance at the 1% (5%) [10%] levels.

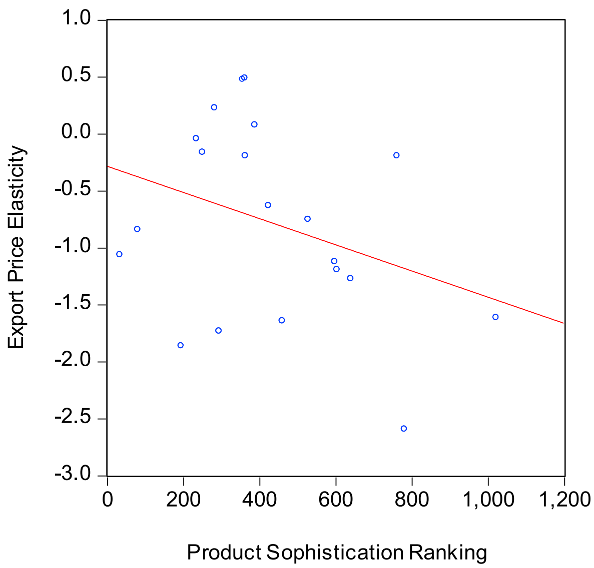

Fig. 2. The relationship between product complexity and export price elasticities for U.S. exports to the world.
Note: The figure shows the relationship between the product complexity ranking (PCR) for individual HS categories obtained from Hausmann et al. (2014) and the export price elasticities (EPE) for the same categories estimated in this paper. The predicted relationship is negative. The line in the figure is from the following regression (with heteroscedasticity and autocorrelation consistent standard errors in parentheses):

$$\underset{}{EPE} = \underset{(0.38)}{-0.28} - \underset{(0.0006)}{0.0012}PCR$$

Adjusted R-squared = 0.060, Standard Error of Regression = 0.83.

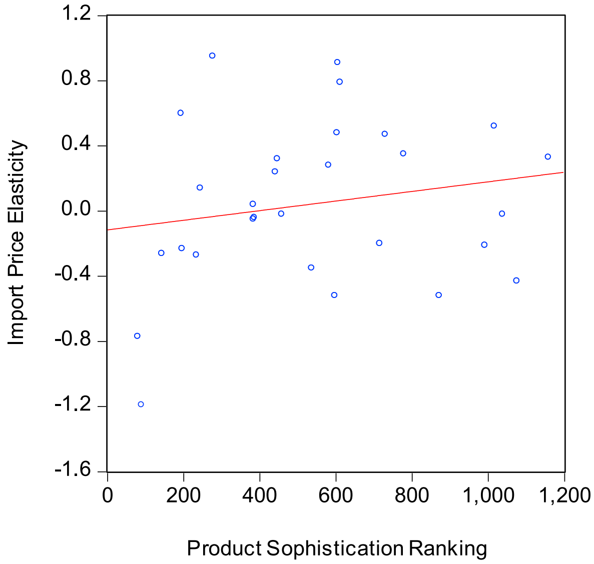

Fig. 3. The relationship between product complexity and import price elasticities for U.S. imports from the world.
Note: The figure shows the relationship between the product complexity ranking (PCR) for individual HS categories obtained from Hausmann et al., 2014 and the import price elasticities (IPE) for the same categories estimated in this paper. The predicted relationship is positive. The line in the figure is from the following regression (with heteroscedasticity and autocorrelation consistent standard errors in parentheses):

$$\underset{}{IPE} = \underset{(0.30)}{-0.12} + \underset{(0.0004)}{0.0003}PCR$$

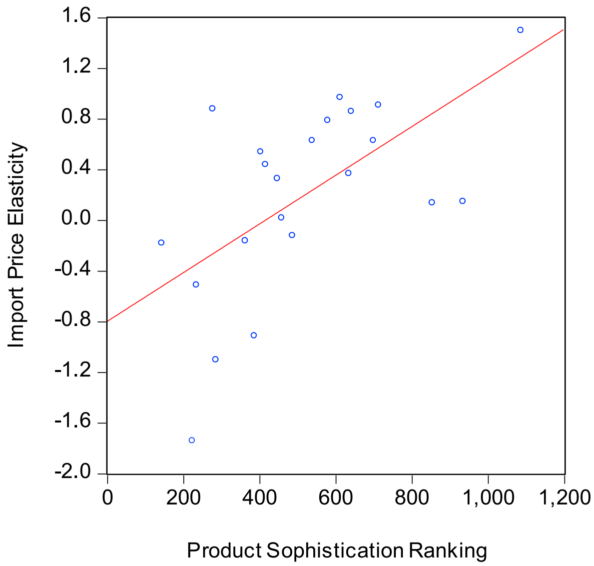

Fig. 4. Adjusted R-squared = -0.002, Standard Error of Regression = 0.50.
The relationship between product complexity and import price elasticities for U.S. imports from China.
Note: The figure shows the relationship between the product complexity ranking (PCR) for individual HS categories obtained from Hausmann et al. (2014) and the import price elasticities (IPE) for the same categories estimated in this paper. The predicted relationship is positive. The line in the figure is from the following regression (with heteroscedasticity and autocorrelation consistent standard errors in parentheses):

$$\underset{}{IPE} = \underset{(0.49)}{-0.79} + \underset{(0.0008)}{0.0019}PCR$$

3. The exchange rate exposure of sectoral stock returns

3.1. Data and methodology

One can investigate how exchange rates affect industry profitability by estimating exchange rate exposures (see, e.g., Bodnar, Dumas, & Marston, 2002, or Dominguez & Tesar, 2006). This involves regressing industry stock returns on exchange rate changes and other

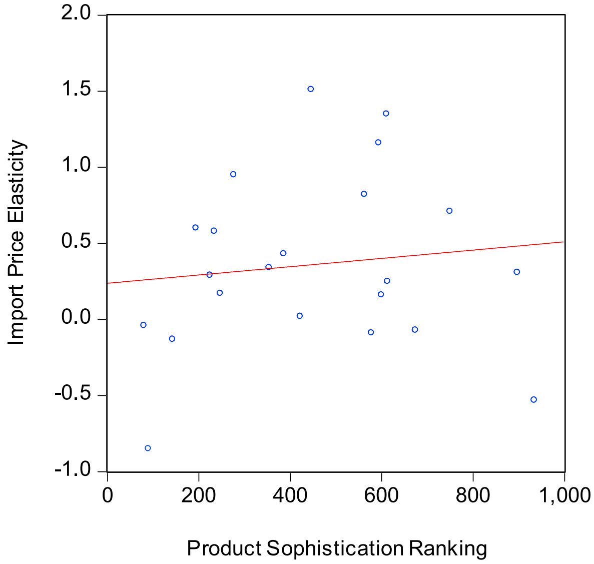

Fig. 5. Adjusted R-squared = 0.336, Standard Error of Regression = 0.622.
The relationship between product complexity and import price elasticities for U.S. imports from countries other than China.
Note: The figure shows the relationship between the product complexity ranking (PCR) for individual HS categories obtained from Hausmann et al., 2014 and the import price elasticities (IPE) for the same categories estimated in this paper. The predictive relationship is positive. The line in the figure is from the following regression (with heteroscedasticity and autocorrelation consistent standard errors in parentheses):

$$\underset{(0.20)}{IPE = 0.24} + \underset{(0.0003)}{0.0003PCR}$$

Adjusted R-squared = -0.035, Standard Error of Regression = 0.587.

variables.

Monthly stock returns for U.S. industries are obtained from the Datastream database. The return on one-month Treasury bills, obtained from Duff and Phelps (2016), is subtracted from industry returns to obtain excess returns. The Federal Reserve broad effective exchange rate, obtained from the Federal Reserve Bank of St. Louis FRED database, is used as the exchange rate variable.

To control for other influences, the three factors used by Fama and French (1993), the five factors used by Chen, Roll, and Ross (1986), and the S&P Goldman Sachs Commodity Index are included in the regression. Fama and French employed the return on the market portfolio, the excess return on small capitalization stocks over large capitalization stocks, and the excess return of value stocks over growth stocks. Chen et al. (1986) employed unexpected inflation, the change in expected inflation, the Treasury bond/Treasury bill spread (the horizon premium), the corporate bond/Treasury bond spread (the default premium) and the monthly growth rate in industrial production. Unexpected inflation in this paper is calculated, following Boudoukh, Richardson, and Whitelaw (1994), as the residuals from a regression of inflation on lagged inflation and current and lagged Treasury bill returns. The change in expected inflation is calculated as the first difference of the expected inflation series. The S&P Goldman Sachs Commodity Index is a weighted average of the prices of industrial metals, precious metals, oil, and agricultural goods. There is a strong relationship between commodity prices and the dollar exchange rate and this can affect the results for commodity-related sectors such as iron and steel. To control for this effect, the commodity index is included.[6]

The regression of industry stock returns on the change in the exchange rate and the control variables is performed over the January 1994 to December 2016 period. There are 276 observations.

3.2. Results

Table 5 presents the results. The adjusted R-squareds average more than 50 percent, which is good for stock return data. A negative coefficient on the exchange rate indicates that an appreciation of the dollar lowers stock returns. The sectors are arranged from the one most harmed by an appreciation to the one most helped by an appreciation.

Metals are exposed to exchange rates. Returns on aluminum stocks fall by 1.15 percent in response to a 1 percent appreciation, returns on nonferrous metal stocks fall by 0.78 percent, and returns on iron & steel stocks fall by 0.60 percent. Paper and forestry are also exposed, with returns on paper and on forestry & paper stocks falling by 1.1 percent in response to a 1 percent appreciation. Between June 2011 and the end of 2015 the dollar appreciated logarithmically by almost 30 percent. The results in Table 5 indicate that

[6] These data to calculate the Fama and French factors are obtained from Professor Kenneth French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). The data to calculate Chen, Roll, and Ross's five factors come from Duff and Phelps 2016 and the FRED database. The data for the S&P Goldman Sachs Commodity Index come from the Datastream database.

Table 5
The exposure of industry stock returns to the exchange rate.

Sector	Exchange Rate Coeff.	HAC Standard Error	Adjusted R-squared	S.E. of Regression
Aluminum	−1.15**	0.50	0.471	0.079
Paper	−1.09***	0.42	0.586	0.061
Forestry & Paper	−1.08***	0.41	0.610	0.058
Ford Motor Co.	−1.06*	0.59	0.355	0.099
Tires	−0.86	0.57	0.448	0.097
Footwear	−0.81**	0.41	0.217	0.072
Nonferrous Metals	−0.78*	0.41	0.485	0.076
Basic Resources	−0.67***	0.23	0.574	0.053
Iron & Steel	−0.60**	0.30	0.514	0.069
Commercial Vehicles &Trucks	−0.56**	0.25	0.598	0.049
Automobiles	−0.52	0.42	0.484	0.073
Commodity Chem.	−0.50**	0.23	0.631	0.040
Basic Materials	−0.47***	0.18	0.686	0.035
Beverages	−0.43**	0.20	0.310	0.039
Auto Parts	−0.42	0.26	0.607	0.043
Aerospace	−0.34	0.24	0.561	0.040
Computer Hardware	−0.33	0.24	0.663	0.047
Clothing & Accessories	−0.33	0.31	0.462	0.052
Consumer Staples	−0.32**	0.15	0.469	0.027
Food Products	−0.31	0.20	0.355	0.031
Specialty Chemicals	−0.27	0.23	0.577	0.036
Building Materials/Fixt.	−0.18	0.20	0.660	0.038
Telecomm. Equip	−0.16	0.21	0.720	0.047
Distillers & Vintners	−0.13	0.31	0.242	0.049
Medical Equipment	−0.12	0.19	0.466	0.034
Oil & Gas	−0.09	0.18	0.642	0.033
Biotechnology	−0.09	0.30	0.425	0.06
Furnishings	−0.06	0.34	0.578	0.053
Brewers	0.06	0.20	0.198	0.049
Consumer Discretionary	0.07	0.12	0.818	0.021
Pharmaceuticals	0.19	0.15	0.440	0.034
Toys	0.35	0.31	0.220	0.059
Semiconductors	0.44	0.30	0.570	0.065
Apparel Rtl	0.56*	0.32	0.400	0.060

Notes: The table reports the coefficient on the exchange rate in a regression of industry stock returns on the exchange rate, the three Fama and French (FF) (1993) factors, the five Chen, Roll, and Ross (CRR) (1986) factors, and the S&P Goldman Sachs Commodity Index. The exchange rate is the Federal Reserve broad effective exchange rate. The FF factors are the return on the market portfolio, the excess return on small capitalization stocks over large capitalization stocks, and the excess return of value stocks over growth stocks. The CRR factors are unexpected inflation, the change in expected inflation, the Treasury bond/Treasury bill spread, the corporate bond/Treasury bond spread, and the growth rate in industrial production.

appreciations such as these can devastate the profitability of the aluminum, iron & steel, paper, and forestry sectors.

The results for automobile stocks are mixed. For auto stocks themselves, the coefficient equals −0.52 and is not significant. This coefficient may be reduced by the presence of American affiliates of foreign companies such as Toyota and Honda in the index. It might be informative to examine the two largest domestic automakers, General Motors and Ford. General Motors stock data are unavailable from Datastream until October 2010, perhaps because GM was in bankruptcy. Ford data are available over the whole sample period. Table 5 indicates that the exchange rate coefficient on Ford stocks equals −1.06 and is significant at the 10 percent level. For commercial vehicles and trucks the coefficient equals −0.56 and is significant at the 5 percent level.

The coefficient on footwear equals −0.81 and is statistically significant. This large value perhaps reflects the finding in Table 2 that a 10 percent exchange rate appreciation causes a 15 percent increase in footwear imports from China. Thus import-competing firms in this sector are exposed to a stronger dollar.

Pharmaceuticals, medical equipment, and biotechnology stocks are not exposed to the dollar. This could reflect the fact that these are sophisticated, research-intensive sectors that possess market power.

Apparel stocks benefit from a stronger dollar. This sector may benefit from appreciations because it imports products from abroad to sell to domestic consumers.

In general, the results in Table 5 indicate that the manufacturing sector is harmed by a stronger dollar. Twenty-eight of the coefficients are negative and only six are positive. Of the negative coefficients, 13 are significant at at least the 10 percent level while of the positive coefficients only one is significant.

The important implication of these results is that if demand for safe dollar assets or currency manipulations keeps the dollar stronger, it will reduce the profitability of the manufacturing sector. It will also benefit sectors that import from abroad and sell to U.S. consumers.

4. Conclusion

The U.S. dollar has been strengthened by international demand for safe U.S. assets and by currency manipulation. This paper investigates how a stronger dollar affects the U.S. manufacturing sector. The results indicate that both U.S. industries that export goods and U.S. industries that compete against imports are affected by exchange rates. Exports of automobiles, aluminum, iron & steel, wood & pulp, and paper tumble in response to a stronger dollar. However, exports of pharmaceuticals are not affected by exchange rates. Imports from China of footwear, sports equipment, radios, lamps, watches, clocks, and aluminum all rise in response to a stronger exchange rate. Imports of unsophisticated products from China tend to increase more than imports of complex products when the dollar appreciates. For countries other than China, imports of electrothermal appliances, radios, furniture, bedding, lamps, miscellaneous manufactures, aluminum, and automobiles all increase significantly when the dollar appreciates. Pharmaceutical imports, on the other hand, are insensitive to exchange rates.

Examining how the dollar affects industry stock returns, many of the same sectors whose trade is sensitive to exchange rates also have high stock market exposures to the dollar. Returns on aluminum stocks, motor vehicle stocks, footwear stocks, nonferrous metal stocks, iron & steel stocks, paper stocks, and forestry stocks are all roiled by appreciations. Eighty percent of the industries examined exhibit negative relationships between stock returns and dollar appreciations, and only one out of thirty-four sectors show a statistically significant positive relationship between stock returns and the dollar. As with exports and imports, there is no evidence from stock return data that the pharmaceutical industry is harmed by a stronger dollar.

Investigating the effect of exchange rates on employment by sector is beyond the scope of this paper. It is interesting to note, though, that the pharmaceutical sector that exhibited no exposure to dollar appreciations in Tables 1, 2, 4 and 5 also experienced 28 percent employment growth between January 1992 and December 2016. On the other hand, highly exposed sectors experienced large drops. For instance, aluminum employment dropped 52 percent between January 1992 and December 2016, paper employment dropped 54 percent, and iron and steel employment dropped 71 percent. Future research should examine how exchange rates affect sectoral employment.

The results in this paper shed light on previous findings. Chinn (2010) noted that estimating import demand is challenging. Other studies have also found that price elasticities are small and income elasticities are large for U.S. imports. In line with these findings, the results in Table 2 for imports from all countries are mixed. However, when imports are disaggregated into those from China and those from other countries, most of the price elasticities are of the expected signs and many are significant. The income elasticities for imports from all countries except China are also reasonable while the income elasticities for imports from China are large. The fact that U.S. GDP and U.S. imports from China have both increased rapidly may artificially inflate the estimated income elasticities in U.S import functions for China. Thus future work should consider disaggregating U.S. imports between those from China and those from the rest of the world when estimating trade elasticities.

The U.S manufacturing sector has been devastated by imports from China (see, e.g., Acemoglu et al., 2014). The results in this paper indicate that if the renminbi is undervalued relative to the dollar, U.S. manufacturing firms can reduce their exposure to Chinese imports by producing more sophisticated products. This strategy would also work for imports from other emerging economies with undervalued exchange rates and for U.S. exports.

U.S. manufacturing imbalances are driving protectionist pressures. Che, Lu, Schott, and Tao (2016) reported that counties in the U.S. that are more exposed to competition from China are also much more likely to support politicians who advocate protectionism. Feigenbaum and Hall (2015) found that economic shocks to U.S. congressional districts from Chinese import competition caused legislators to vote in a more protectionist manner. In December 2017 the U.S. Commerce Department self-initiated antidumping (AD) and countervailing duty (CVD) cases that many viewed as protectionist against Chinese aluminum imports (see Pesek, 2017). It was the first time the Commerce Department had self-initiated AD and CVD cases since 1985, when it initiated cases against semiconductors from Japan. In 1985, protectionist pressures arose not only from AD and CVD cases but also from 99 protectionist bills that legislators introduced to Congress (Destler, 1986). To deflect those pressures, France, Germany, Japan, the U.K., and the U.S. agreed in the Plaza Accord to depreciate the dollar.

If the dollar is overvalued and if the demand for protectionism intensifies, the U.S. and its trading partners should consider negotiating a similar accord involving more countries. In doing so, they should focus on multilateral trade balances and real effective exchange rates rather than bilateral trade balances and bilateral exchange rates. America's trading partners could also lower the dollar by promoting other currencies such as the euro, the yen, and the renminbi as alternative reserve currencies (Freund, 2017). The results in this paper as well as the findings of Arize (2017, pp. 75–84) and others indicate that a weaker dollar would help to rebalance manufacturing trade. It would also relieve pressure on U.S. industries such as aluminum without requiring the use of antidumping and countervailing laws and other forms of administrative protection.

Declarations of interest

None.

Acknowledgments

I thank an anonymous referee for valuable comments. I also thank Sebastian Bustos, Ricardo Hausmann, Masayuki Morikawa, Ljubica Nedelkoska, Frank Neffke, Alessio Terzi, Erik Thorbecke, Makoto Yano, and other colleagues for helpful suggestions. Any errors are my own responsibility. This paper is part of the RIETI project entitled East Asian Production Networks, Trade, Exchange Rates, and Global Imbalances and is supported by the JSPS Grants-in-Aid for Sceintific Research (B, 17H02532).

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.iref.2018.06.002.

References

Acemoglu, D., Autor, D., Dorn, D., Hanson, G., & Price, B. (2014). *Import competition and the great US employment sag of the 2000s*. National Bureau of Economic Research. NBER Working Paper No. 20395.

Arbatli, E., & Hong, G. H. (2016). *Singapore's export elasticities: A disaggregated look into the role of global value chains and economic complexity*. International Monetary Fund. IMF Working Paper WP/16/52.

Arize, A. E. (2017). A convenient method for the estimation of ARDL parameters and test statistics: USA trade balance and real effective exchange rate. *International Review of Economics & Finance, 50*(C), 75–84.

Autor, D., Dorn, D., & Hanson, G. (2013). The China Syndrome: Local labor market effects of import competition in the United States. *The American Economic Review, 103*(6), 2121–2168.

Bartram, S. M., & Bodnar, G. M. (2007). The exchange rate exposure puzzle. *Managerial Finance, 33*(9), 642–666.

Bartram, S. M., Brown, G. W., & Minton, B. A. (2010). Resolving the exposure Puzzle: The many facets of exchange rate exposure. *Journal of Financial Economics, 95*(2), 148–173.

Bergsten, C. F., & Gagnon, J. E. (2017). *Currency conflict and trade policy: A new strategy for the United States*. Washington DC: Peterson Institute for International Economics.

Bodnar, G. M., Dumas, B., & Marston, R. C. (2002). Pass-through and exposure. *The Journal of Finance, 57*(1), 199–231.

Boudoukh, J., Richardson, M., & Whitelaw, R. (1994). Industry returns and the Fischer effect'. *The Journal of Finance, 49*(5), 1595–1616.

Caballero, R., Farhi, E., & Gourinchas, P.-O. (2015). *Global imbalances and currency wars at the ZLB*. National Bureau of Economic Research. NBER Working Paper 21670.

Che, Y., Lu, Y., Schott, P., & Tao, Z. (2016). *Does trade liberalization with China influence U.S. Elections*. National Bureau of Economic Research. NBER Working Paper No. 22178.

Chen, N., Roll, R., & Ross, S. (1986). Economic forces and the stock market. *Journal of Business, 59*(3), 383–403.

Cheung, Y.-W., Chinn, M., & Qian, X. (2015). China-US trade flow behavior: The implications of alternative exchange rate measures and trade classifications. *Review of World Economics, 152*(1), 43–67.

Chinn, M. (2010). *Supply capacity, vertical specialization and trade Costs: The implications for aggregate U.S. Trade flow equations, mimeo*. Madison: University of Wisconsin.

Destler, I. M. (1986). *American trade Politics: System under stress*. Washington D.C: Institute for International Economics.

Dominguez, K. M. E., & Tesar, L. L. (2006). Exchange rate exposure. *Journal of International Economics, 68*(1), 188–218.

Duff, & Phelps. (2016). *2016 SBBI yearbook. Stocks, bonds, bills, and inflation*. Hoboken, New Jersey: John Wiley & Sons.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics, 33*(1), 3–56.

Feigenbaum, J. J., & Hall, A. B. (2015). How legislators respond to localized economic shocks: Evidence from Chinese import competition. *The Journal of Politics, 77*(4), 1012–1030.

Freund, C. (2017). Three ways to reduce a trade deficit', Peterson institute for international economics trade & investment policy watch, February 8. Available at: www.piie.com.

Gruber, J., McCallum, A., & Vigfusson, R. (2016). The dollar in the U.S. International transactions (USIT) model, Board of Governors of the Federal Reserve IFDP notes, November 6. Available at: www.federalreserve.gov.

Hausmann, R., Hidalgo, C. A., Bustos, S., Coscia, M., Simoes, A., & Yildirim, M. A. (2014). *The atlas of economic complexity*. Cambridge, MA: The MIT Press.

Hidalgo, C. A., & Hausmann, R. (2009). The building blocks of economic complexity. *Proceedings of the National Academy of Sciences, 106*(26), 10570–10575.

Johansen, S., Mosconi, R., & Nielsen, B. (2000). Cointegration analysis in the presence of structural breaks in the deterministic trend. *The Econometrics Journal, 3*(2), 216–249.

Mead, D. (2014). Analyzing alternatives to export price indexes. *Beyond the Numbers: Global Economy, 3*(27), 1–5.

Montalvo, J. G. (1995). Comparing cointegrating regression Estimators: Some additional Monte Carlo results. *Economics Letters, 48*(3–4), 229–234.

Orcutt, G. (1950). Measurement of price elasticities in international trade. *The Review of Economics and Statistics, 32*(2), 117–132.

Perron, P. (1989). The great crash, the oil price shock and the unit root hypothesis. *Econometrica, 57*(6), 1361–1401.

Perron, P., & Vogelsang, T. J. (1993). The great crash, the oil price shock and the unit root hypothesis: Erratum. *Econometrica, 61*(1), 248–249.

Pesaran, H., Shin, Y., & Smith, R. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics, 16*(3), 289–326.

Pesek, W. (2017). Odds of a Trump trade war just increased', Nikkei Asian Review, december 4. Available at: asia.nikkei.com.

Petri, P. A., & Plummer, M. G. (2009). The triad in Crisis: What we learned and how it will change global cooperation. *Journal of Asian Economics, 20*(6), 700–713.

Pierce, J., & Schott, P. (2016). The surprisingly swift decline of U.S. manufacturing employment. *The American Economic Review, 106*(7), 1632–1662.

Stock, J., & Watson, M. (1993). A simple estimator of cointegrating vectors in higher order integrated systems. *Econometrica, 61*(4), 783–820.

Thorbecke, W. (2017). Rebalancing trade in East Asia: Evidence from the electronics industry. *Emerging Markets Finance and Trade, 53*(12), 2696–2705.