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Exchange Rate Pass-Through into U.K. Import Prices: Evidence from Disaggregated Data

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Abstract

In this paper we estimate the rate of exchange rate pass-through (ERPT) into U.K. import prices using disaggregated data at the SITC-2 and SITC-3 digit levels. We show that the ERPT varies at the disaggregate level. Because of this heterogeneity at the disaggregate level, the estimate of the ERPT using aggregate data is found substantially upward-biased in our U.K. data. The upward bias exaggerates the impact of exchange rate movements on the competitiveness of imported goods relative to domestically produced goods. Further, we investigate the source of the heterogeneity of the ERPT at the disaggregate level. The industry-specific inflation rate is found significant in explaining this heterogeneity. Finally, we find a significant reduction in estimated ERPT since 1995. Unlike some previous studies, our results suggest that the decrease of the ERPT is correlated with the increased economic stability in the U.K. during the last decade.

JEL codes: F3; F4; C33
Keywords: Exchange rate pass-through; aggregation bias; structural breaks

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Exchange rate pass-through (ERPT) is the percentage change in local-currency import prices as a result of a 1 percent change in the exchange rate between importing and exporting countries. A one-to-one response of import prices to exchange rate changes is known as "complete" ERPT, while a less than one-to-one response of import prices to exchange rate changes is known as "partial" or "incomplete" ERPT. The early work on this topic started in the trade literature and generally uses disaggregate, industry-level data. For instance, see Knetter (1993), Feenstra (1989), Gross and Schmitt (2000), Takeda and Matsuura (2003), and Yang (1997).[1] The focus of these studies is to test the market segmentation and the pricing power of firms. A general conclusion of the work is that ERPT is incomplete and varies across industries. Following Campa and Goldberg (2005), there has been a surge of interest in estimating ERPT into aggregate price indexes. For instance, see Choudri and Hakura (2001), Bailliu and Fujii (2004), and Sekine (2006). ERPT at the aggregate price level is also found to be incomplete and has decreased since the 1990s.

In this paper, we estimate ERPT into U.K. import prices at both aggregate and disaggregate levels. We use a dataset available at the Bank of England, which contains free-on-board (FOB) import prices of the U.K. at the two-digit or three-digit SITC levels.[2] We estimate ERPT both with the aggregate price index and with the industry-level prices. The contribution of this paper is threefold. First, given that ERPT varies across industries, we find that long-run ERPT estimated from the aggregate data is substantially upward-biased. Pesaran and Smith (1995) provide the theoretical foundation for this finding. They show that the heterogeneity leads to an upward bias in a dynamic heterogeneous panel estimate.[3]

Import prices rise when the importing country's currency depreciates. As a result, imports become less competitive compared with domestically produced goods. The upward-biased ERPT of import prices obtained from aggregate data overestimates the increase of import prices in the face of a depreciation. In this case, it overstates the impact of exchange rate movements on the competitiveness of imports relative to domestic products, although the biased ERPT can still provide a "correct" relationship between the exchange rate movements and the inflation rate at the aggregate level. Depending on what policy question we are interested in, our finding suggests that more caution should be exercised in interpreting the ERPT obtained from the aggregate data.

Second, in the study of the heterogeneity of ERPT across industries, we find industry-level ERPT is positively correlated with the industry-specific inflation rate. There are a couple of potential reasons the inflation rate level affects ERPT. Devereux (2006) and Devereux and Yetman (2003) argue that price flexibility depends on the aggregate inflation rate. In an industry with a high inflation rate, firms have to change prices more frequently than otherwise to avoid deviating too much from the optimal price. Changing prices frequently allows firms to react to transitory exchange rate movements and hence increase ERPT.[4] Another argument is from John Taylor (2000). He shows that the persistence of the inflation rate increases with the inflation rate level. When the inflation rate is more persistent, it is costly to be inactive in changing prices. So the persistence of the inflation rate may also increase the frequency of changing prices and therefore increase ERPT. Our finding here is consistent with these predictions.

Third, we find that ERPT into U.K. import prices declined in the 1990s and the decline was likely caused by the more stable macroeconomic environment. ERPT has decreased in both industrial and developing countries since the 1990s.[5] The decrease in aggregate ERPT may come through two channels. Some industries have higher ERPT than others. If the weight of the high-ERPT products in total imports decreases, the aggregate ERPT declines even if the ERPT for each industry remains the same. In contrast, the decrease of the aggregate ERPT may come from a decline of ERPT at the industry level. Campa and Goldberg (2005) show that, on average for OECD countries, the decrease in the aggregate ERPT mainly comes from the first channel. They argue that commodity products, such as petroleum, generally have high ERPT. The OECD countries import fewer of those products after the 1990s, so aggregate ERPT decreases. However, our results suggest this is not the case for the U.K. We find a significant decrease in aggregate ERPT even after excluding energy products from our sample. We also detect a decrease in ERPT for most

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[1] Goldberg and Knetter (1997) provide an excellent review of the literature.

[2] Under free-on-board, the seller pays for transportation of the goods to the port of shipment, plus loading costs. FOB prices are good measures of import prices because they do not include transportation and other costs that are incurred in the U.K.

[3] Imbs, Mumtaz, Ravn, and Rey (2005) use the same theory to explain the purchasing power parity puzzle.

[4] In this argument, we assume the prices are set in local currency; that is, the British pound. This pricing strategy is also used in Betts and Devereux (2000) and Devereux and Engel (2003).

[5] Campa and Goldberg (2005) find ERPT decreases in OECD countries. Sekine (2006) confirms this finding in six major industrial countries with a time-varying parameter model. See Frankel, Parsley, and Wei (2005) for an example of developing countries.

industries in our sample. More importantly, we follow Campa and Goldberg (2005) to construct a variable to measure the decrease in aggregate ERPT due to the change of import structure. This variable has only a negligible contribution to the decrease in aggregate ERPT.[6] Instead, we find that the decrease in ERPT is correlated with the more stable macroeconomic environment, which suggests that stabilizing monetary policy during the last decade played an important role in the decrease of ERPT.

For a better understanding of the reduction in ERPT, it seems necessary to have a model with deeper microstructure that incorporates the interaction between the firm's pricing behavior and aggregate variables such as ERPT and monetary policy. There has recently been a surge in such studies using goods-level micro price data. Gopinath and Rigobon (2008) document that price stickiness for U.S. imports has increased significantly since the 1990s. The increase of import price stickiness may contribute to the decline of ERPT during the same period. Gopinath, Itskhoki, and Rigobon (2010) find that the ERPT of U.S. import prices depends on the currency of pricing. Gopinath and Itskhoki (2010) document that long-run ERPT is positively correlated with the frequency of price adjustment. They find that a dynamic menu cost-model matches the finding better than Calvo and state-dependent pricing models with constant demand elasticity. Other studies on import prices using micro data include Nakamura and Steisson (2009) and Neiman (2010), among others.

The rest of the paper is structured as follows. In Section 1, we present our data and discuss our results for estimated ERPT rates. Section 2 attempts to explain the variation in estimated ERPT rates across industries, while in Section 3, we try to explain the time variation on estimated ERPT rates. Section 4 summarizes our main findings.

1. ERPT INTO DISAGGREGATED IMPORT PRICES

In this section, we estimate the ERPT rates into U.K. import prices at the industry level in the following equation:

$$\Delta p_{i,t} = c_i + \phi_i \Delta s_t + \gamma_i \Delta w_t^* + \eta_i \Delta d_t + \Sigma_{j=1}^{J} \xi_{i,j} \Delta p_{i,t-j} + \nu_{i,t}. \tag{1}$$

All variables are in logs and $\Delta x_t = x_t - x_{t-1}$ in our notation. The left-hand-side variable, $p_{i,t}$, is the local currency price of imports in industry i. On the right-hand side, c_i is a constant. Other right-hand-side variables include the exchange rate, s_t, exporters' cost variable, w_t^*, the real GDP of the importing country, d_t, and the error term, $\nu_{i,t}$. The coefficient ϕ_i is the ERPT coefficient for industry i. ERPT is complete if $\phi_i = 1$ and incomplete if $\phi_i < 1$.

We use quarterly data from first quarter 1984 to first quarter 2004. Our dataset includes FOB import price indexes of 57 U.K. industries at the two-digit or three-digit SITC level (source: Office of National Statistics), classified into nine sectors defined at the one-digit SITC level.[7] These import price indexes are obtained from a survey completed by industrialists. c_i is the industry-specific constant with which we aim to capture any industry-specific effects. Due to data limitations, we do not control for differences in exporters' cost of production across industries.[8] Thus, the cost variable, w_t^*, in Equation (1) does not have the subscript i. Following Campa and Goldberg (2005), we construct a consolidated exporter partners' cost proxy. The cost variable is measured by the unit labor cost of the foreign country that is calculated from $W_t^* = \frac{NEER_t ULC_t}{REER_t}$, where ULC_t is the U.K. unit labor cost, $NEER_t$ is the sterling nominal effective exchange rate, and $REER_t$ is the sterling real effective exchange rate deflated by unit labour cost. All of these three variables are obtained from the International Financial Statistics dataset of the IMF. This provides us with a measure of the U.K.'s trading partners' costs, where each partner is weighted by its importance in U.K. trade.[9] The real GDP of the importing country is used as a proxy for the total demand in the importing country. s_t is the sterling NEER. We include lagged import prices in the equation, with the number of lags determined by the Akaike Information Criteria (AIC). This ad hoc specification aims to capture the reluctance of firms to adjust prices quickly, implying gradual adjustment of import prices to changes in exchange rates. Finally, the coefficient, ϕ_i, is the short-run ERPT rate for industry i, and $\Xi_i = \frac{\phi_i}{1-\Sigma_{j=1}^{J}\xi_{i,j}}$ is the long-run ERPT rate for the same industry.

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[6] In our regression, this variable is insignificant at any conventional significance level in explaining the decrease of aggregate ERPT.

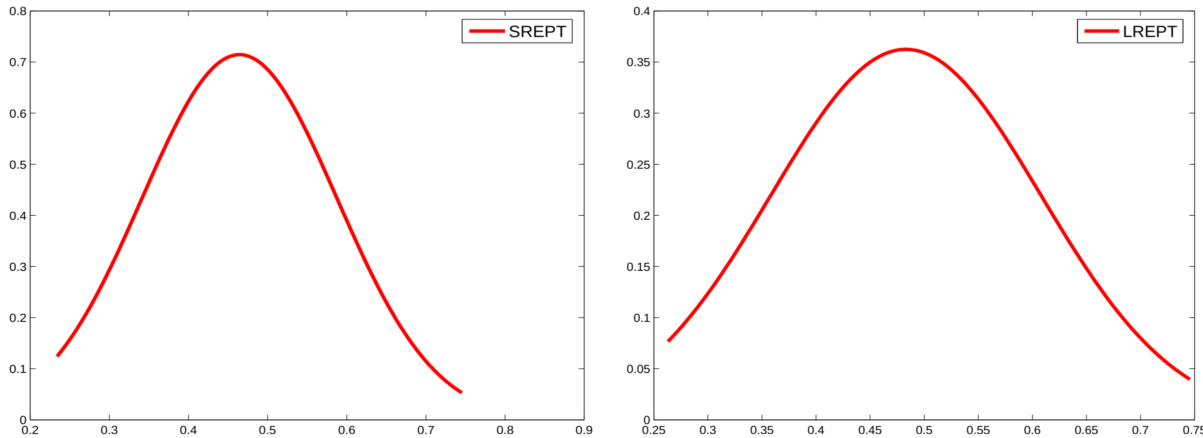
[7] FOB import prices do not include transportation and distribution costs. The inclusion of such costs would bias ERPT estimates downward since these costs are not affected by exchange rate changes.

[8] Similarly, a commodity-specific nominal effective exchange rate is more appropriate for our estimation at disaggregate levels. We do not consider such exchange rates due to data unavailability.

[9] Corsetti, Dedola, and Leduc (2005) find that the inclusion of a variable controlling for marginal cost variations can significantly reduce the estimation bias caused by the endogeneity problem.

We illustrate the estimation results from this regression in Figure 1, which plots the normalized probability distribution of the estimated ERPT rates (that are statistically significant) at the industry level. The panels show the distribution of ERPT rates across industries.

Figure 1: Industry-Specific ERPT Rates



NOTE: The figure shows the distribution of estimated short- and long-run ERPT rates across industries.

We tabulate the estimation results in more detail in Table 1. The table lists the industries in our dataset and the respective one-digit SITC classification under which they are listed. Notice that we do not have data at the industry level for SITC 4 (Oil & Fats). The estimation results suggest that the estimated short- and long-run ERPT rates vary significantly across industries: We can clearly reject the hypothesis that the estimated ERPT rates are identical across industries, based on a likelihood ratio test on the homogeneity of ϕ_i, i.e. $\phi_i = \phi$.[10]

Next, we group our industries under four import categories: Food (SITC 0 and 1), Raw Materials (SITC 2), Energy (SITC 3), and Manufacturing (SITC 4, 5, 6, 7, and 8). Then we estimate ERPT rates at the level of these import categories:

$$\Delta\bar{p}_{k,t} = c_k + \phi_k \Delta s_t + \gamma_k \Delta w_t^* + \eta_k \Delta d_t + \Sigma_{j=1}^{J} \Delta\xi_{k,j}\bar{p}_{k,t-j} + \bar{\nu}_{k,t}. \quad k = 1,..,4, \tag{2}$$

where k denotes one of the four sectors and $\bar{p}_{k,t} = \sum_{i=1}^{n_k} m_i^k p_{i,t}^k$ is the aggregated U.K. import price index obtained by taking a weighted average over industries that fall under sector k. The number of those industries is denoted by n_k. We weight each industry's import price with that industry's trade weight in the sector under which it is listed. That is, the weight of industry i in sector k equals the ratio of the volume of imports in industry i to the total volume of imports in sector k. These results are shown in columns 2 and 5 in panel A of Table 2. For purposes of comparison, we have two other estimates for ERPT rates at the sectoral level. These are obtained by taking an unweighted average (shown in columns 3 and 6 in panel A), and weighted average (shown in columns 4 and 7 in panel A) of industry-specific ERPT rates estimated by Equation (1) across industries that fall under the respective sector. In panel A, the finding that ERPT varies across industries is robust under different estimation methods. In addition, the estimates from the trade-weighted and unweighted averages are similar. So the trade weight is not important in explaining the aggregation bias, which we will discuss shortly.

A number of results are immediately apparent. First, most product categories in our sample exhibit partial ERPT, both in the short run and long run. Starting with the short-run estimates, for each import category except energy, we reject the hypothesis of zero ERPT. For these sectors, we also reject the hypothesis of complete pass-through. Turning to the long-run estimates, for food and manufacturing, we reject the hypotheses of zero and complete pass-through. For the raw materials sector, however, the findings are inconclusive: Due to large standard errors attached to these estimates, we fail to reject either zero or complete pass-through. For the energy sector, the estimated pass-through rates are not significantly different from zero. This result is surprising since we would expect homogenous products, such as those listed under the energy sector, to have pass-through rates close to 1. One important aspect of products listed under the energy sector is that they are traded in international commodity markets in U.S. dollars. Hence, a more relevant exchange rate for these products is the dollar–sterling rate. Therefore, we reestimated ERPT rates

[10] We obtain a test statistic of 199.1955 with a p value of 0.000. This is the Swamy test for coefficient homogeneity.

Table 1: Industry-Specific Estimates of Short- and Long-Run ERPT Rates

	Short run	Long run
SITC 0: Total Food & Live Animals	–	–
Live Animals	0.83 (0.54)	0.55 (0.55)
Meat & Meat Prep.	0.33 (0.10)	0.36 (0.17)
Dairy Products & Eggs	0.41 (0.08)	0.49 (0.34)
Fish	0.64 (0.09)	0.69 (0.15)
Cereals & Cereal Prep.	0.41 (0.13)	0.37 (0.19)
Fruit & Vegetables	0.23 (0.14)	0.15 (0.11)
Sugar, Sugar Prep. & Honey	0.37 (0.12)	0.44 (0.19)
Coffee, Tea, Cocoa, etc.	0.41 (0.15)	0.56 (0.38)
Animal Feeding Stuff	0.67 (0.17)	0.83 (0.40)
Misc. Edible Products & Prep.	0.25 (0.20)	0.18 (0.20)
SITC 1: Total Beverages & Tobacco	–	–
Beverages	0.35 (0.09)	0.40 (0.28)
Tobacco	0.55 (0.20)	0.45 (0.36)
SITC 2: Total Crude Materials	–	–
Wood, Lumber & Cork	0.55 (0.13)	0.80 (0.34)
Pulp & Waste Paper	0.58 (0.19)	0.94 (0.74)
Textile Fibers	0.41 (0.13)	0.93 (0.47)
Metal Ores	-0.12 (0.21)	-0.10 (0.17)
SITC 3: Mineral Fuels & Related Materials	–	–
Oil	0.03 (0.51)	0.03 (0.61)
Oil Products	-0.01 (0.41)	-0.01 (0.47)
SITC 4: Oils (Animal & Vegetable) & Fats	–	–
SITC 5: Chemicals & Related Products	–	–
Organic Chemicals	0.52 (0.10)	0.78 (0.30)
Inorganic Chemicals	0.16 (0.22)	0.10 (0.18)
Coloring Materials	0.63 (0.20)	0.79 (0.49)
Medical Products	0.08 (0.07)	0.09 (0.11)
Toilet Prep.	0.61 (0.07)	0.73 (0.34)
Plastics	0.26 (0.08)	0.40 (0.19)
Residual Chemicals	0.52 (0.10)	0.68 (0.30)
SITC 6: Material Manufactures, Incl. Precious Stones	–	–
Leather	0.11 (0.15)	0.10 (0.18)
Rubber	0.34 (0.09)	0.38 (0.15)
Wood & Cork	0.46 (0.13)	0.46 (0.18)
Paper & Paperboard	0.29 (0.05)	0.55 (0.35)
Textile Fabrics	0.44 (0.06)	0.68 (0.26)
Minerals, Excl. Precious Stones	0.38 (0.05)	0.40 (0.10)
Iron & Steel	0.07 (0.08)	0.13 (0.19)
Non-Ferrous Metals	0.14 (0.14)	0.23 (0.28)
Non-Ferrous Metals, Excl. Silver	0.13 (0.15)	0.21 (0.27)
Misc. Metal Manufacturers	0.51 (0.07)	0.54 (0.26)
SITC 7: Machinery & Transport Equipment	–	–
Machinery	0.42 (0.05)	0.61 (0.36)
Mechanical Machinery: Consumption	0.50 (0.15)	0.32 (0.17)
Mechanical Machinery: Intermediate	0.53 (0.08)	0.51 (0.26)
Mechanical Machinery: Capital	0.64 (0.08)	0.66 (0.12)
Electrical Machinery: Intermediate	0.32 (0.06)	0.48 (0.16)
Electrical Machinery: Consumption	0.30 (0.08)	0.24 (0.17)
Electrical Machinery: Capital	0.23 (0.05)	0.36 (0.18)
Road Vehicles	0.54 (0.05)	0.82 (0.44)
Other Road Vehicles: Consumption	0.75 (0.19)	0.53 (0.26)
Other Road Vehicles: Intermediate	0.59 (0.10)	0.56 (0.30)
Other Road Vehicles: Capital	0.53 (0.08)	0.64 (0.32)
Other Transport Equipment	0.14 (0.08)	0.16 (0.14)
Railway Equipment: Intermediate	0.21 (0.24)	0.17 (0.24)
Railway Equipment: Capital	0.08 (0.43)	0.09 (0.54)
SITC 8: Misc. Finished Manufactures	–	–
Clothing	0.41 (0.17)	0.37 (0.24)
Footwear	0.55 (0.11)	0.41 (0.20)
Scientific & Photographic: Consumption	0.24 (0.12)	0.13 (0.10)
Scientific & Photographic: Intermediate	0.55 (0.15)	0.46 (0.25)
Scientific & Photographic: Capital	0.47 (0.13)	0.45 (0.34)
Residual Misc. Manufactures: Consumption	0.43 (0.10)	0.54 (0.24)
Residual Misc. Manufactures: Intermediate	0.41 (0.05)	0.37 (0.08)
Residual Misc. Manufactures: Capital	0.27 (0.16)	0.13 (0.10)

NOTES: The table shows industry-specific short- and long-run ERPT rates across industries. White standard errors are in parentheses.

Table 2: Estimated Short- and Long-Run ERPT Rates

	Short run			Long run		
	AGGR	UW	TW	AGGR	UW	TW
Panel A:						
SITC 0-1: Food	0.38†	0.45†	0.38†	0.42†	0.45†	0.39†
	(0.08)	(0.17)	(0.13)	(0.18)	(0.28)	(0.23)
SITC 2: Raw Materials	0.30†	0.35†	0.29†	0.46‡	0.64‡	0.50‡
	(0.14)	(0.16)	(0.17)	(0.39)	(0.43)	(0.36)
SITC 3: Energy	0.02	0.01	0.02	0.02	0.01	0.02
	(0.47)	(0.46)	(0.48)	(0.56)	(0.54)	(0.56)
SITC 5-8: Manufacturing	0.43†	0.38†	0.42†	0.63†‡	0.42†	0.54
	(0.04)	(0.12)	(0.08)	(0.33)	(0.24)	(0.28)
Panel B:						
SITC 0-8: All	0.44†	0.38†	0.38†	0.66†	0.43†	0.49†
	(0.06)	(0.14)	(0.12)	(0.19)	(0.27)	(0.30)

NOTES: The table reports the estimated short- and long-run ERPT rates at the sectoral level (panel A) and for the overall economy (panel B). In columns 2/5, we report the estimates of the short-run/long-run pass-through rates based on aggregate import price data. In columns 3/6 and 4/7, we report the unweighted and trade-weighted averages of industry-specific short-run/long-run pass-through rates. White standard errors are in parentheses. † Significantly different from 0 at a 10 percent confidence level. ‡ Not significantly different from 1 at a 10 percent confidence level.

for this sector using the dollar–sterling rate in place of the sterling NEER. The point estimates of the short- and long-run ERPT rates remain insignificant in this alternative specification.[11] However, we prefer not to place too much weight on this particular result because the energy sector in our sample has only two industries listed under it and this might render ERPT estimates for this sector unreliable.[12] As for the overall pass-through estimates (panel B), the evidence suggests partial pass-through both in the short run and long run, perhaps reflecting the relatively large weight of the manufacturing sector in U.K. imports. In general terms, our results are fairly similar to those reported in Campa and Goldberg (2005). That is, they also find partial ERPT for the food and manufacturing sector, both in the short run and long run over the period 1975–2003. In addition, their findings suggest incomplete pass-through for the raw materials sector over this period as well.

Aggregation Bias

As we have mentioned, the estimated short- and long-run ERPT rates vary significantly across industries in our dataset. This heterogeneity, however, has been totally ignored in the literature of estimating the ERPT with the aggregate price index. Equation (3) is generally used in this literature:

$$\Delta\overline{p}_t = c + \phi\Delta s_t + \gamma\Delta w_t + \eta\Delta d_t + \Sigma_{j=1}^{J}\xi_j\Delta\overline{p}_{t-j} + \overline{\nu}_t, \tag{3}$$

where $\overline{p}_t$ is the trade-weighted import price index. According to Pesaran and Smith (1995), the estimate of long-run ERPT will be upward-biased and inconsistent if the heterogeneity exists at the disaggregate level. We will use a simple example to illustrate the reason. $\overline{p}_t = \sum_{i=1}^{N} w_i p_{i,t}$ denotes the aggregate U.K. import price index obtained by taking a trade-weighted average over all industries (N = 57 in our dataset), and c is the regression constant. Consider the case where only short-run ERPT varies across industries. Let $\phi_i = \phi + \tau_i$, where we assume τ_i to be a zero-mean random variable. Then, aggregating the data implies that, in regressions, this heterogeneity is pushed into the residual term. This can be seen by substituting $\phi_i = \phi + \tau_i$ into equation (1) and rearranging the resulting equation to obtain:

$$\Delta\overline{p}_t = c + \phi\Delta s_t + \gamma\Delta w_t + \eta\Delta d_t + \Sigma_{j=1}^{J}\xi_j\Delta\overline{p}_{t-j} + (\overline{\nu}_t + \tau_i\Delta s_t). \tag{4}$$

From (4), it is clear that $E[(\overline{\nu}_t + \tau_i\Delta s_t)\Delta s_t] \neq 0$. Moreover, if Δs_t is serially correlated, the error term will also be serially correlated, implying that the OLS estimates of the coefficients will be biased and inconsistent. Note that instrumental variable estimation does not solve the problem because any instrument that is correlated with Δs_t would also be correlated with the error term.[13] Pesaran and Smith (1995) show

[11] Campa and Goldberg (2005) also first report an insignificant ERPT for the energy sector. However, the estimate becomes significant after using the exchange rate relative to the U.S. dollar. We cannot duplicate this result in our sample of the U.K.

[12] As shown in Table 1, these two industries are Oil and Oil Products.

[13] This argument would also hold if there were heterogeneity among the estimated coefficients on the lagged dependent variable.

that if the true data-generating process is heterogeneous and the assumption of homogeneity is imposed on the coefficients of the panel (for instance, in a fixed-effects model), the estimates of short-run coefficients will be biased downward, while the autoregressive coefficients will be biased upward. The authors also show that under these conditions, the estimates of long-run coefficients will be biased upward. The authors propose the mean group estimator to solve this problem. The mean group estimator of aggregate short- and long-run ERPT rates can be obtained by taking an unweighted average of the estimates of industry-specific ERPT as shown below:[14]

$$\begin{aligned}\hat{\phi}_{MG} &= \frac{1}{N}\sum_{i=1}^{N}\hat{\phi}_i \\ \hat{\Xi}_{MG} &= \frac{1}{N}\sum_{i=1}^{N}\hat{\Xi}_i = \frac{1}{N}\sum_{i=1}^{N}\frac{\hat{\phi}_i}{1-\sum_{j=1}^{J}\hat{\xi}_{i,j}}. \end{aligned} \tag{5}$$

If the number of industries and the length of sample are sufficiently large, the mean group estimator will be unbiased and consistent. In panel B of Table 2, we compare the mean group estimates of the aggregate ERPT rates to those obtained by estimating (3). The panel shows that estimated long-run ERPT based on the aggregate import price index is substantially larger than the corresponding mean group estimate.[15] But the estimate of short-run ERPT is found to be similar across estimation methods in our dataset. This finding suggests that the bias in the aggregate estimates of long-run ERPT seems to stem from the estimated coefficients on the lags of the dependent variable. The mean group estimate suggests that the sum of the estimated coefficient on the lagged dependent variable is 0.03; this sum is estimated to be 0.33 when aggregate data are used. This result is consistent with Pesaran and Smith (1995) and Robertson and Symons (1992). The authors show that averaging data in heterogeneous panels may lead to an upward bias in the estimates of persistence.

Equation (5) provides an unbiased estimate of how much import prices change in response to exchange rate movements. It can be used to measure the impact of exchange rate movements on the competitiveness of imports. The higher the ERPT, the more expensive the imported products after a depreciation of the British pound. As a result, imports become less competitive relative to the products made in the U.K. The upward-biased ERPT from aggregate data will overestimate the effects of exchange rate movements on the competitiveness of imported products.

2. THE CROSS-SECTIONAL VARIATION IN ESTIMATED ERPT RATES

In previous sections, we argued that ERPT rates vary substantially across industries. But what explains this cross-sectional variation? In this section, we try to shed some light on this issue.

What Causes ERPT Rates to Vary Across Industries?

The following models are estimated in order to understand the factors that lead ERPT rates to vary across industries:

$$\hat{\phi}_i = c_s + \kappa_s Z_i + e_i \tag{6}$$

$$\frac{\hat{\phi}_i}{1-\sum_{j=1}^{J}\hat{\xi}_{i,j}} = c_l + \kappa_l Z_i + \varsigma_i, \tag{7}$$

where the industry-specific short- and long-run ERPT rates are obtained from the first-stage OLS regressions described above.[16] Here, we consider only the pass-through coefficients that are statistically significant.

[14] We find similar results using trade-weighted averages of the estimates of industry-specific ERPT.

[15] This result is preserved even when we correct for the small sample bias in the autoregressive coefficient. Following Pesaran and Zhao (1999), we use nonparametric bootstrap methods to correct for the small sample bias present in the estimated long-run coefficients. The bias-corrected mean group estimate for the long-run aggregate ERPT rate is 0.46; it is 0.70 when we use the aggregated import price data. In addition, correcting for cross-sectional correlation does not alter the results greatly. For example, a SURE-Mean Group estimator produces a long-run pass-through estimate of 0.43.

[16] Frankel, Parsley, and Wei (2005) conduct a similar exercise for a multicountry panel. They consider the impact of cross-country differences by adding interactions of the nominal exchange rate and country characteristics in the first-stage pass-through regression. This is a possible alternative to the two-step approach adopted here. Note, however, that our approach allows us to cleanly examine the issues in a sequential manner. Our first-stage regression identifies significant cross-sectional heterogeneity, while the second-stage regressions reported in this section attempt to explain this heterogeneity.

The matrix Z_i contains variables that reflect characteristics of different industries. The choice of variables included in Z_i is similar to that in Yang (1997). Specifically, Z_i includes the following five variables:

Capital-to-labor ratio (KLR). Industries with a high capital-to-labor ratio may find it harder to change their output because it is usually more difficult to acquire capital than labor, especially in the short run. Thus, industries with a high capital-to-labor ratio tend to have high elasticity of marginal cost with respect to output. In other words, industry-specific capital-to-labor ratios can be used as a proxy for the output elasticity of marginal cost. This elasticity will be positive if the underlying cost function is convex. That is, the marginal cost of production will increase when output produced increases. A depreciation in the importing country's currency makes the local currency price of imports relatively more expensive, which, in turn, reduces the demand for imports. Under the assumption of a convex cost function, a reduction in output lowers the marginal cost of production and the price of imports. Hence, the increase in the price of imports, following the depreciation, is partially offset. The higher the elasticity of marginal cost with respect to output, the larger this offset will be. Therefore, we expect industries with higher capital-to-labor ratios to have lower ERPT rates.

Data on capital and labor are obtained from the Bank of England industry dataset. The dataset covers 34 industries for the period 1969 to 2000. The data include capital in buildings, computers, intangibles (excluding software), plant and machinery (excluding software and communications), communications equipment, vehicles, and software. The data on labor are total hours worked (not adjusted for quality). We use the average capital-to-labor ratio over this period for each industry.

Intraindustry trade (IIT). IIT is defined as

$$IIT_{i,t} = 1 - \frac{|X_{i,t} - M_{i,t}|}{X_{i,t} + M_{i,t}}, \tag{8}$$

where $M_{i,t}$ and $X_{i,t}$ are calculated as the quarterly averages of import and export volumes in industry i. IIT is an import component in international trade, especially among the industrialized countries.[17] In the trade literature, IIT has been associated with product differentiation.[18] Yang (1997) shows that ERPT is positively correlated with IIT. The intuition is, with everything else equal, the higher the IIT, the more differentiated the products. Therefore, firms have more monopoly power and can pass to consumers more cost changes due to exchange rate variations.

The quarterly data on import and export volumes run from first quarter 1984 to first quarter 2004 and cover eight U.K. sectors (at the one-digit SITC level) and 57 U.K. industries (at the two- or three-digit SITC levels). The source for these data is the Office of National Statistics (ONS).

Change in demand elasticity (CDE). In models of monopolistic competition, where each monopolistic competitor is assumed to be too small to affect the aggregate price level, the price elasticity of demand facing each firm will be constant. However, when it is assumed that each firm is large enough to affect the industry price, the demand elasticity facing any individual firm will be a function of prices charged by other firms. One implication of this is that ERPT rates in each industry would be related to price-induced movements in that industry's demand elasticity. Hence, the difference in ERPT rates across industries, to some extent, can be explained by differences across industries in how the price elasticity of demand moves with movements in price. The level of IIT in each industry can be used as a proxy for the price elasticity of demand in that industry. As noted above, high levels of IIT can be linked to high degrees of product differentiation and low substitution elasticity, and the price elasticity of demand tends to be low when the degree of substitution is low. Therefore, the estimated coefficient from a regression of $(1 - IIT_{i,t})$ on $p_{i,t}$ in each industry can provide us with a measure of the sensitivity of demand elasticity to price movements in each industry. That is,

$$ln\epsilon_{i,t} = c_i + \psi_i p_{i,t} + \omega_{i,t}, \tag{9}$$

where we use $\epsilon_{i,t}$ to denote the price elasticity of demand in industry i, and we proxy this demand elasticity by $(2 - IIT_{i,t})$. We use 2 for convenience in taking logarithms. $p_{i,t}$ is the (log) import price index of industry i at time t. $\omega_{i,t}$ is the error term with a mean of zero and a constant variance. $\hat{\psi}_i$ is our proxy for the response of demand elasticity to price movements in industry i.[19] We expect industries with higher $\hat{\psi}_i$ to be associated with higher ERPT rates.

[17] See Ruffin (1999) for more details.

[18] See, for instance, Krugman (1981), Helpman (1981), and Chiarlone (2000).

[19] In our sample, the correlation coefficient between the variables IIT and DE is 0.2 both in the short run and long run.

Tariff (TRF). We include industry-specific tariff rates to capture the impact of trade barriers on ERPT rates. We assume exporters who face high tariff rates will face a higher degree of local competition in the markets to which they export and, hence, will be more limited in passing on exchange rate changes to the prices they charge. Therefore, we expect industries protected with higher tariff rates to have lower rates of ERPT. Tariff rates are obtained from the United Nations Conference on Trade and Development.

Inflation (INF). We include industry-specific average inflation rates to capture the impact price rigidities might have on ERPT rates. It is documented, for instance, in Taylor (2000) that when inflation is high, it is more likely to be persistent. This implies that forward-looking firms could be more willing to pass on cost changes to their prices in an environment with high and persistent inflation. Hence, we expect higher inflation to be associated with higher ERPT rates.

Estimation results from (6) and (7) are shown in Table 3. The first/second row presents our results when the short-run/long-run ERPT rates estimated from the first round of regressions are used as the dependent variable after eliminating any statistically insignificant estimates. The table shows that the variable INF is significant (at a 1 percent confidence level) with the correct sign in explaining the cross-sectional variation across estimated short- and long-run ERPT rates. All other variables are found to be insignificant.

Table 3: Cross-Sectional Variation in ERPT Rates

	CDE	INF	KLR	TRF	IIT	R^2	N
Short-run ERPT	0.07	0.14	0.02	0.001	- 0.05	0.27	41
	(0.09)	(0.04)	(0.10)	(0.001)	(0.08)		
Long-run ERPT	- 0.35	0.21	- 0.10	-0.0003	0.003	0.47	22
	(0.13)	(0.05)	(0.13)	(0.005)	(0.08)		

NOTES: This table reports the results from regressing estimated short- and long-run ERPT rates on industry-specific capital-to-labor ratio (KLR); volume of intraindustry trade (IIT); change in demand elasticity (CDE); tariff rate (TRF); and inflation rate (INF). White standard errors are in parentheses.

3. THE TIME VARIATION IN ESTIMATED ERPT RATES

In this section, we relax the assumption that ERPT is constant over time and explore the possibility of structural breaks over our sample.

Testing for the Stability of the Estimated ERPT Rates

In this section, we focus on estimated short-run ERPT rates because the time-series variation in the estimated long-run ERPT rates would also capture any time-series variation in the estimated coefficients on the lagged dependent variable. Two methods are employed to test for a structural change. The first method employs the Andrews (1993) test for structural break with an unknown break point. We estimate the unknown break date for industry-specific short-run ERPT rates calculated using Equation (1). The left panel of Figure 2 plots the distribution of dates where a structural break is detected in the estimated industry-specific short-run ERPT rates. The x axis is the break date, and the y axis is the number of industries for which a break is detected. We ignore any estimated dates before 1990 and after 1998 because small sample problems deem them unreliable. First quarter 1995 appears to be the most important break date across our panel.

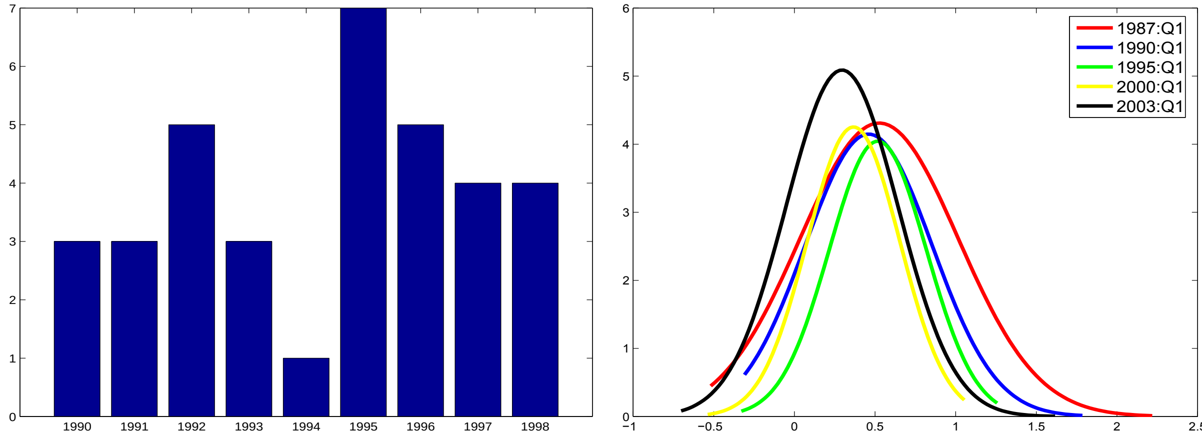
The second method considers a simple time-varying parameter model. That is, we estimate the time-varying ERPT coefficients via a simple random coefficients model that allows these coefficients in Equation (1) to vary over time. The unobservable parameters are assumed to follow a driftless random walk and are estimated via the Kalman filter. The right panel of Figure 2 plots the kernel densities of estimated short-run ERPT rates across industries at different dates that we chose randomly. The estimates indicate that the ERPT of import prices decreases substantially over time.

The results are similar when we apply the two methods to the aggregate import price index. The structural break test indicates a change in the estimated aggregate short-run ERPT coefficients in first quarter 1995.[20] This result is consistent with that obtained using the disaggregated data. Figure 3 plots the estimated aggregate short-run ERPT coefficient over time using a simple time-varying parameter model

[20] The Sup F statistic rejects the hypothesis of stability at the 10 percent level (p value 0.09). The estimated break date is first quarter 1995.

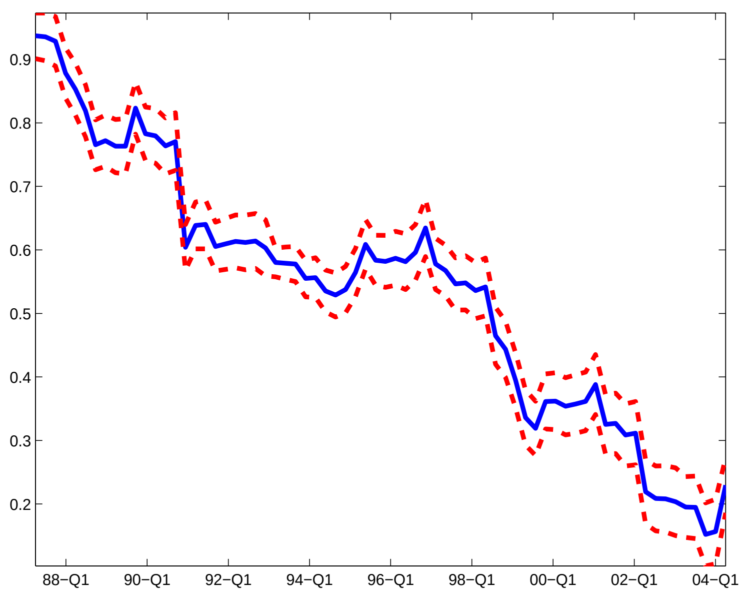
with standard errors around it. As in the disaggregated data, estimated short-run ERPT declines over the sample period.[21]

Figure 2: Short-Run ERPT Rates Over Time: Disaggregated Import Price Data



NOTES: The left panel shows the distribution of dates for which a break is detected in the estimated short-run ERPT rates across industries. The x axis is the break date, and the y axis is the number of industries for which a break is detected. The right panel shows the kernel densities of the estimated short-run ERPT rates across industries at selected dates.

Figure 3: Short-Run ERPT Rates Over Time: Aggregate Import Price Data



NOTES: The figure plots the estimated aggregate short-run ERPT coefficient over time using a simple time-varying parameter model. The dotted lines are the standard errors.

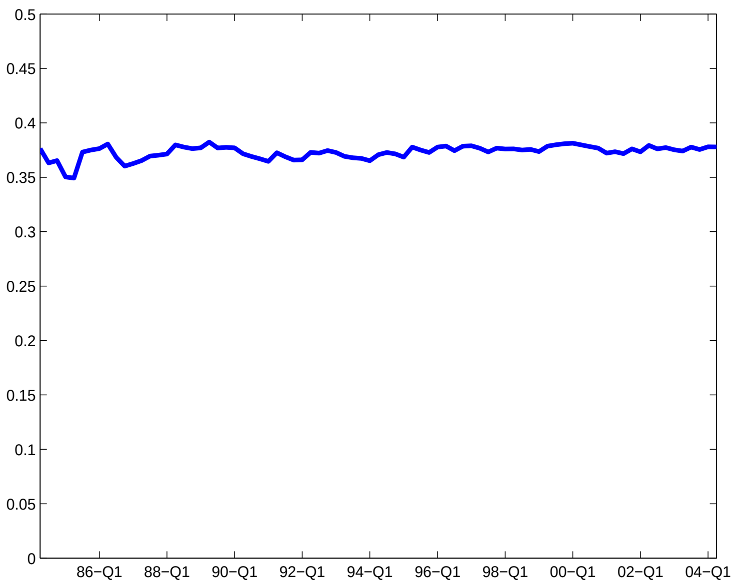
What Can Lead to a Change in ERPT Rates Over Time?

What can explain this decline in ERPT rates? To answer this question, we focus on the aggregate import price data because the estimated variation in the pass-through is broadly consistent across the aggregate and disaggregated data. Specifically, we regress our estimates of the time-varying short-run aggregate ERPT rates on the following variables:

[21] Note that 1995 is characterized by a change in ONS conventions regarding import price data. Before 1995, the ONS published import price data based on unit value indexes. After 1995, the ONS based data on company quotes. This raises the possibility that the structural break test may be picking up this change in the definition of the import price index. However, the fact that the time-varying parameter model indicates a gradual decline in ERPT over the entire sample casts doubt on this idea.

Structure of imports (impute). One simple explanation for the decline in estimated ERPT rates over time could be a change in the composition of imports. If the share of sectors with low pass-through rates increases over time, the aggregate ERPT declines even if all ERPT rates remain the same at disaggregate levels. Campa and Goldberg (2005) argue this is the major reason we observe a decrease in ERPT among OECD countries. As in Campa and Goldberg, we construct an index, impute, that reflects the change in estimated short-run ERPT rates due to a change in the weights attached to each industry over time. In each period, this variable is set equal to the trade-volume-weighted average of industry-specific short-run ERPT rates estimated using Equation (1). Hence, a decrease in the index reflects an increase in the weight of industries with low pass-through rates. In Figure 4, we plot this variable against time.[22] The figure reveals that the decline in the ERPT rate caused by a shift in the import structure is negligible for our dataset.

Figure 4: Structure of Imports



NOTES: The figure shows the trade-volume-weighted average of industry-specific short-run ERPT rates. A decrease in the index reflects an increase in the weight of industries with low pass-through rates.

Macroeconomy. The ERPT literature suggests that stable monetary policy and low exchange rate volatility can lead to lower pass-through rates. This is because importing countries with high macroeconomic stability are likely to have their currencies chosen for international transactions or because greater macroeconomic stability is likely to make importers less willing to change prices. In order to proxy the stability of the macroeconomy, we use in our regressions the conditional variance of the exchange rate returns, consumer price index (CPI) inflation, and import price inflation, all estimated using the exponentially weighted moving average (EWMA) method as well as the rate of GDP growth in the importing country.[23]

Exchange rate surprise. The estimated errors from an AR(4) model fitted to the sterling NEER are used as a proxy for the unexpected changes in the exchange rate. The idea is to determine whether errors in forecasting the exchange rate have played a part in the reduction of ERPT rates in the post-1995 period. For example, if an appreciation in the exchange rate is greater than expected, the ERPT rate may decline if firms reduce prices to offset the effects of the unexpected change in the exchange rate.

The first column of Table 4 shows our benchmark specification. Not surprisingly, the coefficient on impute is insignificant, indicating that the fall in the ERPT rate cannot be explained by a change in the structure of imports in our sample. We find the coefficient of the variance of import price inflation to be significant (at 1 percent) and positive. However, the exchange rate variance has a negative significant coefficient, suggesting that a fall in this variable has increased the ERPT rate. This might be due to the high correlation coefficient (0.87 for our sample) between the variance of the exchange rate and import price

[22] In our sample, the impute variable has a mean of 0.37 and a standard deviation of 0.01.

[23] We do not include the variance of GDP growth as a proxy for macrostability in our regressions since this variable is highly correlated with the variance of import price inflation in our sample.

inflation. In order to mitigate the effects of multicollinearity, the third column presents the estimates when we exclude the import price inflation variance from the regression. The coefficient on the variance of the exchange rate is now positive and significant (at 1 percent). This implies that the decrease in exchange rate variance over the 1990s reduced pass-through to import prices. The coefficient on GDP is also positive and significant (at 1 percent). When we run our regressions excluding the exchange rate variance instead, we find only import price inflation to be significant (at 1 percent) with a positive sign. However, the coefficient on the variance of CPI inflation and on our proxy for unexpected exchange rate changes is not found to be significant in any of the three specifications in our sample.

Table 4: Time Series Variation in ERPT Rates

		Excluding IMP inflation variance	Excluding ER variance
GDP	- 0.775 (1.347)	6.883 (1.726)	- 0.348 (1.521)
Impute	- 0.441 (2.050)	- 1.383 (3.906)	- 0.091 (2.202)
ER variance	- 0.061 (0.016)	0.112 (0.016)	–
IMP inflation variance	0.380 (0.024)	–	0.289 (0.014)
CPI inflation variance	0.040 (0.112)	0.152 (0.210)	- 0.046 (0.130)
ER surprise	- 0.003 (0.003)	- 0.007 (0.005)	- 0.004 (0.003)
Adj. R^2	0.92	0.70	0.90
N	70	70	70

NOTES: The table shows the results from regressing the estimated time-varying short-run aggregate ERPT rates on the rate of GDP growth in the importing country, the variance of the exchange rate (ER variance), the variance of import price inflation (IMP inflation variance), the variance of CPI inflation (CPI inflation variance), and a measure of unexpected exchange rate changes (ER surprise). White standard errors are in parentheses.

Unlike Campa and Goldberg (2005), we find that the decline of ERPT is not caused by the change in import structure. This finding can be confirmed by our two exercises. First, we find the index, impute, does not decrease over time. Indeed, we detect a significant decrease in ERPT at the disaggregate level for most industries. In a study on Japan, Otani, Shiratsuka, and Shirota (2006) find that the decline of ERPT in Japan is mainly caused by the decline of ERPT in each product category.[24] Those results call for a deeper investigation into the interaction between monetary policy and firms' pricing behaviors to understand the decline of ERPT.

4. CONCLUSION

In this paper, we estimate the rate of ERPT into U.K. import prices using disaggregated data at the two- or three-digit SITC level. Consistent with earlier studies, we find evidence for significant heterogeneity in ERPT among the 57 industries involved in our analysis. We demonstrate that this heterogeneity induces substantial estimation bias if we use the aggregate data to estimate ERPT. For instance, when we use an aggregate import price index, we find the short-run/long-run ERPT rate to be 0.44/0.66, but when we use disaggregated data instead, the pass-through rate for the overall economy drops to 0.38/0.43. The upward-biased estimate is misleading when we use it to measure how the competitiveness of local products changes with exchange rate movements. Further, we investigate the source of the cross-sectional variation in the estimated industry-specific pass-through rates. For our sample, we find the industry-specific average inflation rates to be significant in explaining this variation. Finally, we find a significant reduction in estimated ERPT rates since 1995. This decline is detected both at the aggregate and disaggregate levels. Unlike Campa and Goldberg (2005), we find that the change in import structure contributes only negligibly to the decrease of ERPT. Instead, the decrease is highly correlated with increased macroeconomic stability in the U.K. during last decade. This finding suggests that stabilizing monetary policy may play an important role in explaining the decrease of ERPT.

[24] Otani, Shiratsuka, and Shirota (2006), however, did not study if the decline of ERPT is correlated with the macroeconomic environments.

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