Analyzing aggregate real exchange rate persistence through the lens of sectoral data.

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Abstract

In this paper we analyze the persistence of aggregate real exchange rates (RERs) for a group of EU-15 countries by using sectoral data. The tight relation between aggregate and sectoral persistence recently investigated by Mayoral (2008) allows us to decompose aggregate RER persistence into the persistence of its different subcomponents. We show that the distribution of sectoral persistence is highly heterogeneous and very skewed to the right, and that a limited number of sectors are responsible for the high levels of persistence observed at the aggregate level. We use quantile regression to investigate whether the traditional theories proposed to account for the slow reversion to parity (lack of arbitrage due to nontradibilities or imperfect competition and price stickiness) are able to explain the behavior of the upper quantiles of sectoral persistence. We conclude that pricing to market in the intermediate goods sector together with price stickiness have more explanatory power than variables related to the tradability of the goods or their inputs.

Keywords: PPP puzzle, real exchange rates, persistence, heterogeneous dynamics, aggregation bias, nontradability, imperfect competition, pricing-to-market.

1. INTRODUCTION

Most of the empirical literature on purchasing power parity (PPP) and real exchange rate (RER) persistence focuses on the analysis of aggregate RER data, where the latter are constructed with aggregate price indices. After years of close scrutiny, the general consensus is that aggregate RERs may converge to parity in the long run, but that the rate at which this happens is very slow, with half-lives (HL) in the range of 3 to 5 years (Frankel and Rose, 1996, Lothian and Taylor, 1996 and Murray and Papell, 2005). Thus, while the high volatility of real exchange rates could potentially be explained by monetary or financial shocks, the rate of reversion to parity seems to be too slow to be compatible with plausible nominal rigidities, giving rise to the so-called *PPP puzzle* (Rogoff, 1996).

Several avenues have been pursued to shed more light on this issue. A recent literature has focused on the analysis of disaggregate real exchange rates, cf. Crucini and Shintani (2008), Imbs et al. (2005), Crucini et al. (2005), Cheung et al. (2001), Yang (1997), Knetter (1993), etc. One of the common findings of these papers is that there is a considerable degree of heterogeneity across sectors. With respect to sectoral persistence and its relation with that observed at the aggregate level, the empirical findings appear to be disparate. Some authors have found large divergences between sectoral and aggregate reversion rates. Using Eurostat data, Imbs et al. (2005) report standard HL estimates for aggregate RERs, in the range of 3-5 years and considerably lower HL estimates, around 1 year, when sectoral data is employed. They claim that the PPP puzzle arises as a consequence of an *aggregation bias* that affects aggregate estimates due to the high degree of heterogeneity in sectoral RERs which neither standard time series nor panel data techniques are able to control. On the other hand, it has also been pointed out that the *aggregation bias* appears not to be a robust feature in the data. Crucini and Shintani (2008) analyze a micro-panel of local currency prices of individual retail goods and services in major cities and find that the median level of persistence (across goods) is similar to that obtained for the aggregate RER (HL around 12-19 months).

Mayoral (2008) has recently studied the relations between measures of persistence computed at different aggregation levels from a theoretical point of view and her results help to clarify the contrasting empirical findings outlined above. She has shown that there is a tight link between measures of persistence computed at different aggregation levels. In particular, in a linear setting similar to that consider in Imbs et al. (2005) and Crucini and Shintani (2008), the impulse response function (IRF) computed with aggregate data equals the average of the sectoral impulse responses.[1] The same result holds if the scalar measures associated with the IRF, such as the cumulative impulse response, are employed to evaluate shock persistence. Gadea and Mayoral (2008) have used these results to show that, in fact, this relation between IRFs holds very closely for Imbs et al. (2005)'s dataset, implying that aggregate and average sectoral speeds of reversion to parity are very similar.

These theoretical results are the starting point of this paper. They imply that aggregate persistence, as measured by the IRF or the associated scalar tools, is completely determined by the behavior of the sectors, in such a way that the aggregate HL can be consistently estimated by using either aggregate or sectoral data. By using sectoral data, it will be possible to decompose aggregate persistence into the persistence of its different subcomponents, obtaining, thereby, a lot of valuable information about the sources of aggregate persistence. Another interesting implication of these results is that they reveal the nature of the relation between sectoral and aggregate persistence: the aggregate response to a shock is the average of the individual responses and, since averages are very non-robust measures, a situation where most sectors present quick reversion to parity but where a few of them are highly persistent, is compatible with a highly persistent aggregate RER.

The goal of this paper is to shed further light on the causes of the slow reversion to parity of aggregate exchange rates through the analysis of sectoral data. We study European real exchange rates for a group of EU-15 countries for which highly disaggregate price data is available (aggregate prices are broken down into 94 sectors). Our strategy is twofold. Firstly, we analyze and describe the distribution of sectoral shock response and decompose aggregate persistence into the persistence of its different components. This will allow us to

[1] It has also been shown that sectoral heterogeneity does not necessarily induce a bias in aggregate estimates computed using standard time series techniques.

identify interesting features about the sources that determine aggregate persistence and to show that aggregate persistence is determined, to a great extent, by the behavior of sectors in the upper quantiles of the distribution of persistence. Secondly, we investigate more thoroughly the factors that account for the slow reversion to parity. Several theories have been proposed to explain the slow speed of convergence of RERs. Among these theories, the lack of arbitrage in nontradable goods and the existence of imperfect competition due to pricing-to-market have prominent roles. Using data on market structure and international trade, we perform a quantile regression analysis to test these theories. We place special emphasis on explaining the behavior of the upper quantiles of the distribution of sectoral persistence because, as mentioned before, to a large degree, they determine the persistence observed at the aggregate level. Moreover, it is well known that the resulting estimates of various effects on the conditional mean of sectoral persistence are not necessarily indicative of the size and nature of these effects on the upper tail of the distribution. Thus, a more complete picture of covariate effects can be provided by estimating a family of conditional quantile functions.

Our main results can be summarized as follows. Firstly, we document both a high degree of heterogeneity as well as high and positive skewness in the speed of reversion of the sectors so that, although most sectors present moderate persistence, a few of them present extremely slow reversion rates. By decomposing aggregate persistence into the persistence of its different components, we show that the top 30% most persistent sectors account for more than 50% of the aggregate HL. Moreover, the HL of the aggregate of the remaining 70% of the sectors is below 2 years, that is, compatible with models based on nominal rigidities. Sectors belonging to the durable category are the ones that show the lowest speed of reversion to parity: on average, they account for more than 40% of the long-run cumulative effect of shocks to aggregate RERs. We have also explored the conditional distribution of sectors in the upper quantiles. As in the previously mentioned results, the durable category is heavily overrepresented among the top 30% most persistent sectors. On average, its weight within this group exceeds its unconditional weight by 35%. Moreover, the correlation between the "excess weight" that durable goods have in the upper quantiles and the aggregate country HLs is greater than 70%, suggesting a strong relation between aggregate RER persistence and the existence of highly persistent durable goods in the corresponding country.

Secondly, our quantile regression analysis shows that variables related to the price stickiness of the final good and the market structure and the degree of competition of the intermediate inputs have a significant effect on sectoral persistence. Furthermore, the impact of these variables is more important the higher the quantile considered. Interestingly, once the market structure of the intermediate inputs has been taken into account, that of the final goods does not appear to be important in explaining sectoral persistence. Finally, variables related with the tradability of the goods are not significant either, implying that traditional theories that attribute the slow speed of reversion of RERs to the existence of nontraded goods in the consumption basket do not explain EU current trade patterns well. These conclusions are in agreement with modern trade theories (cf. Chari et al., 2002, Carvalho and Nechio, 2008).

The outline of the paper is as follows. Section 2 summarizes the theoretical results about the relation between aggregate and sectoral IRFs and presents the empirical models and the persistence measures that will be employed in the article. Section 3 introduces the different datasets used in this paper and examines whether IRFs estimated with data at different levels of aggregation behave as the theory predicts. Section 4 explores the distribution of sectoral persistence while Section 5 analyzes whether the traditional theories (lack of arbitrage due to nontradability or imperfect competition and price stickiness) are able to explain the distribution of sectoral persistence. Section 6 puts forward some concluding remarks.

2. HETEROGENEITY, AGGREGATION AND PERSISTENCE.

In this section we present the models employed in our empirical exercise as well as the theoretical results that link the persistence of the aggregate real exchange rate to that of the sectors. These results will allow us to decompose aggregate persistence into the persistence of its different subcomponents. We also provide the definitions of the persistence measures that will be used throughout the paper.

2.1. Econometric models for disaggregate and aggregate RERs

Impediments to arbitrage, nominal rigidities and market structure vary considerably across sectors. Since these impediments are usually believed to be behind cross-country price differences, they could bring about important heterogeneity in the speed of reversion to parity across sectors and countries. Heterogeneity in sectoral exchange rates has been widely documented, see, for instance, Imbs et al., (2005) and Crucini and Shintani (2008) for recent references.

We adopt a linear specification for sectoral RERs that incorporates different sources of heterogeneity: in addition to country and sector fixed effects (captured by the parameter $\gamma_{c,i}$), it also allows for different speeds of shock adjustment by letting the autoregressive coefficients of sectoral models be heterogeneous. More specifically, we assume that sector i in country c is given by

$$q_{c,i,t} = \gamma_{c,i} + \sum_{k=1}^{K} \rho_{c,i,k} q_{c,i,t-k} + \nu_{c,i,t}, \qquad \text{for } t = 1, ..., T;\ i = 1, ..., N;\ c = 1, ..., C, \quad (1)$$

where $q_{c,i,t}$ is the real exchange rate for country c, sector i at time t. To simplify the exposition, for now we suppose that $K = 1$ (this hypothesis will be relaxed shortly), so that $q_{c,i,t} = \gamma_{c,i} + \rho_{c,i} q_{c,i,t-1} + \nu_{c,i,t}$. We further assume that $\gamma_{c,i} = \bar{\gamma} + \eta^{\gamma}_{c,i}$ and $\rho_{c,i} = \bar{\rho} + \eta^{\rho}_{c,i}$, where $\bar{\gamma}$ and $\bar{\rho}$ are constants and $\rho_{c,i}$ has support on the interval (-1, 1], that $E_s\left(\rho_c^h\right)$ exists for all h, where $E_s(.)$ denotes the expectation over the cross-sectional distribution of the sectors of country c, and that the innovation $\nu_{c,i,t} = u_{c,t} + \varepsilon_{c,i,t}$ is the sum of two orthogonal, zero-mean martingale difference sequences, one common to all sectors in country c and one idiosyncratic, with variances $\sigma^2_{u_c} > 0$ and $\sigma^2_{\varepsilon_{c,i}}$, respectively. Finally, $\eta^{\gamma}_{c,i}$ and $\eta^{\rho}_{c,i}$ are *i.i.d.* zero-mean random variables, mutually independent of $\nu_{c,i,t}$.

The aggregate real exchange rate for country c, $Q_{c,t}$, can be derived along the lines of Stoker (1984), who defines the aggregate process as the expected value of the disaggregate models. Then

$$Q_{c,t} = E_s(q_{c,t}) = E_s(\gamma_c) + E_s(\rho_c q_{c,t-1}) + E_s(\nu_{c,t}) \tag{2}$$

Under the assumptions above and assuming further that the number of micro-processes is (countably or unaccountably) infinite, Lewbel (1994) showed that expression (2) is equivalent to

$$Q_{c,t} = \sum_{s=1}^{\infty} A_s Q_{c,t-s} + u_{c,t}, \tag{3}$$

for constants A_1, A_2, ... that satisfy $A_j = m_j - \sum_{r=1}^{j-1} m_{j-r} A_r$, where $m_j = E\left(\rho_c^j\right)$ is the moment of order j of ρ_c.

We use models (1) and (2) to fit sectoral and aggregate RERs, respectively. Under sectoral heterogeneity the aggregate model might display very complicated dynamics, as shown by the fact that (2) contains an infinite number of parameters. Berk (1974) showed that consistent estimates of the parameters can be obtained if an AR(k^*) process is fitted to $Q_{c,t}$ such that k^* tends to infinity with the sample size. Moreover, Kursteiner (2005) has shown that if k^* is selected using the general-to-specific approach (Ng and Perron, 1995), the resulting estimators are consistent and asymptotically normal.

2.2. The relation between persistence measures across aggregation levels

There is no consensus in the literature either on the definition of persistence or on the most appropriate tools to measure this property. In this paper, by persistence we refer to the speed and pattern of adjustment of the process of interest to economic shocks of different natures. According to this definition, the IRF provides an accurate description of the trajectory of adjustment to economic shocks and, therefore, it is a suitable way to evaluate persistence. Thus, we now focus on the IRF in order to establish the link between shock persistence at the aggregate and at the sectoral levels.

At the sectoral level, the IRF of sector i in country c can be computed as the difference between two forecasts

$$IRF_{c,i}(t,h) = E\left(q_{c,i,t+h} | u_{c,t} = 1; z_{c,i,t-1}\right) - E\left(q_{c,i,t+h} | u_{c,t} = 0; z_{c,i,t-1}\right), \tag{4}$$

where the operator $E(.|.)$ denotes the best mean squared error predictor and $z_{i,t-1} = \begin{pmatrix} q_{c,i,t-1}, & q_{c,i,t-2} & ... \end{pmatrix}'$; applied to the simple model in (1) with $K = 1$, it yields that the response of sector i in country c to a unitary aggregate shock in t, h periods ahead is

$$IRF_{c,i}(t,h) = \rho_{c,i}^h, \text{ for } h \geq 0. \tag{5}$$

The IRF associated with the aggregate model in (3), denoted as $IRF_{c,aggr}$, can be computed in a similar fashion as

$$IRF_{c,\ aggr}(t,h) = E\left(Q_{c,t+h}|u_{c,t} = 1; Z_{t-1}\right) - E\left(Q_{c,t+h}|u_{c,t} = 0; Z_{t-1}\right), \tag{6}$$

where $Z_{t-1} = (Q_{c,t-1}, Q_{c,t-2}, ...)$. Replacing $Q_{c,t}$ in (6) by its expression in (3), it is obtained that

$$IRF_{c,aggr}\left(t,h\right) = \sum_{j=1}^{h} A_j IRF_{c,aggr}\left(h-j\right), \text{ with } IRF_{c,aggr}\left(0\right) = 1. \tag{7}$$

Mayoral (2008) has shown that there is a tight link between the aggregate IRF and those of the sectors. More specifically, under the previous assumptions, she has shown that

$$IRF_{c,aggr}\left(t,h\right) = E_s\left(IRF_{c,i}(t,h)\right), \tag{8}$$

that is, the aggregate IRF is the expected value of the sectoral impulse responses. For the simple case where $K = 1$, this implies that

$$IRF_{c,aggr}(t,\ h) = E_s\left(\rho_{c,i}^h\right), \text{ for all } h. \tag{9}$$

The relationship between IRFs also holds for values of K larger than 1 and under less stringent assumptions than the ones set above (see Mayoral, 2008).

This result is very interesting for several reasons: firstly, it allows us to decompose the impulse response of the aggregate RER into those of its different subcomponents and, therefore, to isolate the contribution of each sector to the total shock response; and, secondly, it clarifies the nature of the relationship between the aggregate and sectoral IRFs. The aggregate IRF is the average of the micro responses and, since averages are known to be very non robust measures, it follows that an economy where most sectors present moderate persistence and only a few of them are highly persistent is compatible with a very persistent aggregate RER. We will show in Section 4 that this is actually the case, implying that aggregate RER persistence is determined by the behavior of a few but highly persistent sectors.

2.3. Measures of persistence

Since the IRF is an infinite vector of numbers, it is customary to use scalar measures instead. Thus, throughout this article, we employ two of these tools: the half life (HL) and the cumulative impulse response (CIR).

The most commonly used measure in the PPP literature is, by far, the half-life (HL), defined as the number of periods it takes until half of the effect of a shock dissipates. For each country c, the HL is defined as the value of the IRF that satisfies

$$IRF_{c,aggr}(t, h = HL_c) = 0.5. \tag{10}$$

Using equality (8), the HL can also be computed as $E_s\left(IRF_{c,i}(t, h = HL_c)\right) = 0.5$. We follow Kilian and Zha (2002) and define the half-life as the largest value of HL_c such that $\mathrm{IRF}_{c,aggr}\left(t, HL_c - 1\right) \geq 0.5$ and $\mathrm{IRF}_{c,aggr}\left(t, HL_c + 1\right) < 0.5$.

In spite of its popularity, the HL presents important shortcomings, the most severe one being that it cannot be consistently estimated in general AR(p) models. This is because, when $p > 1$, the HL is not a continuous function of the model parameters, so small changes in the latter can bring about abrupt changes in the value of the HL. This translates into a lack of consistency of HL estimates for the general case.

Another popular measure of persistence, which does not present these problems, is the cumulative impulse response (CIR) that is defined as

$$CIR_c\left(h\right) = \sum_{l=0}^{h} IRF_{c,aggr}\left(t, l\right), \tag{11}$$

or $CIR_c\left(h\right) = \sum_{l=0}^{h} E_s(IRF_{c,i}\left(t, l\right))$, if sectoral data is employed. An interesting feature of this measure is that, by considering different horizons h, it can provide a more complete picture of the pattern of shock adjustment over time. In what follows we will use the CIR evaluated at different time horizons h, corresponding to the short run ($h = 12$ months), medium run ($h = \{24, 36\}$ months) and long run ($h = \{60,84\}$ months).

3. ANALYZING AGGREGATE RER PERSISTENCE USING SECTORAL DATA: EMPIRICAL RESULTS

In this section we describe the data employed in our empirical analysis. After that, we evaluate the persistence of European RERs using both aggregate and disaggregate data. We find similar values as in previous studies, with most half lives of deviations from PPP falling well within the "*consensus view*" of 3 to 5 years reported by Rogoff. We also show that the theoretical results presented in Section 2.2 are a reasonable prediction of the empirical relations between measures of persistence computed with aggregate or sectoral data.

3.1. The data

We use the Eurostat Harmonized Index of Consumer Prices (HICP) for 11 European countries ranging from 1996:1 to 2007:12. These countries and their corresponding abbreviations are Austria (AU), Belgium (BE), Denmark (DK), Finland (FI), France (FR), Germany (GE), Italy (IT), Netherlands (NL), Spain (SP), Sweden (SW) and United Kingdom (UK).[2] Eurostat provides data corresponding to different levels of aggregation. We focus on two of them: the most disaggregate level, that contains prices relative to 94 sectors, and the aggregate HICP indices.[3]

Nominal exchange rates are obtained from the Main Economic Indicators of the OECD. RERs are defined against the U.K. pound as follows

$$q_{c,i,t} = p_{c,i,t} + p_{uk,i,t} - s_{c,t},$$

[2]We originally considered all the EU-15 countries. However, four of these countries (Portugal, Luxembourg, Greece and Ireland) present important data availability limitations for the other datasets employed in this paper. For this reason, we decided to drop them from the analysis.

[3]Price data on some sectors is missing for some countries, see Eurostat for more details.

and

$$Q_{c,t} = P_{c,t} + P_{uk,t} - s_{c,t},$$

where $q_{c,i,t}$ and $Q_{c,t}$ denote sectoral and aggregate RER for country c, $p_{c,i,t}$ ($P_{c,t}$) and $p_{uk,i,t}$ ($P_{uk,t}$) are the logs of the price index of sector i (the log of the overall price index) for country c and the $U.K.$, respectively, and $s_{c,t}$ is the log of the nominal exchange rate between country c and the UK.

In order to account for the persistence of European exchange rates, we also employ three additional datasets: the Comtrade (United Nation Commodity Trade Statistic Database), the OECD Structural Analysis Statistics (STAN, Edition 2008) and the Input-Output Tables (IOT) from the OECD. The first of these provides information about trade flows for individual countries at six digits of disaggregation and allows us to calculate different indicators that capture the trade features of each sector. The second contains data about value added, gross output, labor costs and other industry indicators that will be employed to analyze the market structure of the sectors. Finally, the IOT allows us to determine the type and proportion of inputs employed in the production of the final goods in our price dataset. More details on these databases are provided in Appendix 1.

3.2. Persistence in European RERs

We now evaluate the persistence of aggregate real exchange rates using the tools introduced in Section 2.3. To do this, we have estimated the aggregate IRF using both aggregate and sectoral data.

More specifically, the following procedure has been followed. Firstly, two slightly different aggregate RERs have been considered: one constructed using the original aggregate price indices provided by Eurostat and the other where price indices are the weighted average of the available sectoral price data.[4] These series are not identical, mainly because data on some sectors are missing. In both cases, AR(p) processes have been fitted to the data,

[4] To aggregate the available sectoral prices, the weights employed are the average over the period 1996-2007 of those used by Eurostat to aggregate sectoral prices.

where p was chosen according to the general-to-specific approach (GTS). Since RERs are, in general, highly persistent, Kilian's (1998) bootstrap after bootstrap method has been employed to correct for the small sample bias that standard estimates of AR coefficients suffer in this case. Next, estimates of the IRF, denoted as $\widehat{IRF_{aggr}}_{\_0}$ and $\widehat{IRF_{aggr}}_{\_1}$ according to whether the original aggregate price indices or the weighted average of sectoral prices are used to construct RERs, have been obtained following (7).

Estimates based on sectoral data have been obtained in a similar way. AR(p) processes have been fitted to all sectoral RERs in country c, where p has been chosen using the GTS approach. Bias-corrected estimates of the AR coefficients have been plugged into (4) to obtain estimates of sectoral IRFs. Next, using relation (8), the estimated aggregate IRF computed with sectoral data, denoted as $\widehat{IRF}_{\text{sect}}$, has been obtained as the weighted average of the sectoral IRFs.[5]

Figure I presents the plots of $\widehat{IRF_{aggr}}_{\_0}$, $\widehat{IRF_{aggr}}_{\_1}$ and $\widehat{IRF}_{\text{sect}}$. These graphs show that European RERs are highly persistent. Interestingly, they also show that estimates of the IRFs based on aggregate or sectoral data are, in general, very similar, as predicted by the theoretical results in Section 2.2. Confidence bands (denoted as CB) at the 5% significance level have been computed using bootstrap techniques for the three IRFs and, in all cases, the three IRFs lay within the bands. For the sake of clarity, only the confidence bands relative to $\widehat{IRF_{aggr}}_{\_1}$ are reported, although all of them are quite similar.

Table I displays some summary statistics corresponding to the estimated IRFs, more specifically, the HL and four values of the $\text{CIR}_c(h)$ (for h corresponding to 1, 2, 3 and 5 years). Agg0, Agg1 and Sect correspond to measures obtained from $\widehat{IRF_{aggr}}_{\_0}$, $\widehat{IRF_{aggr}}_{\_1}$ and $\widehat{IRF}_{\text{sect}}$, respectively. The figures in this table corroborate the graphs in Figure I: in general, the values of the different measures of aggregate persistence computed with

[5]The weights are those employed to aggregate sectoral price data, see footnote 4. The maximum value of p, pmax, was set equal to 36 for both aggregate and sectoral data.

aggregate or disaggregate data are very close.

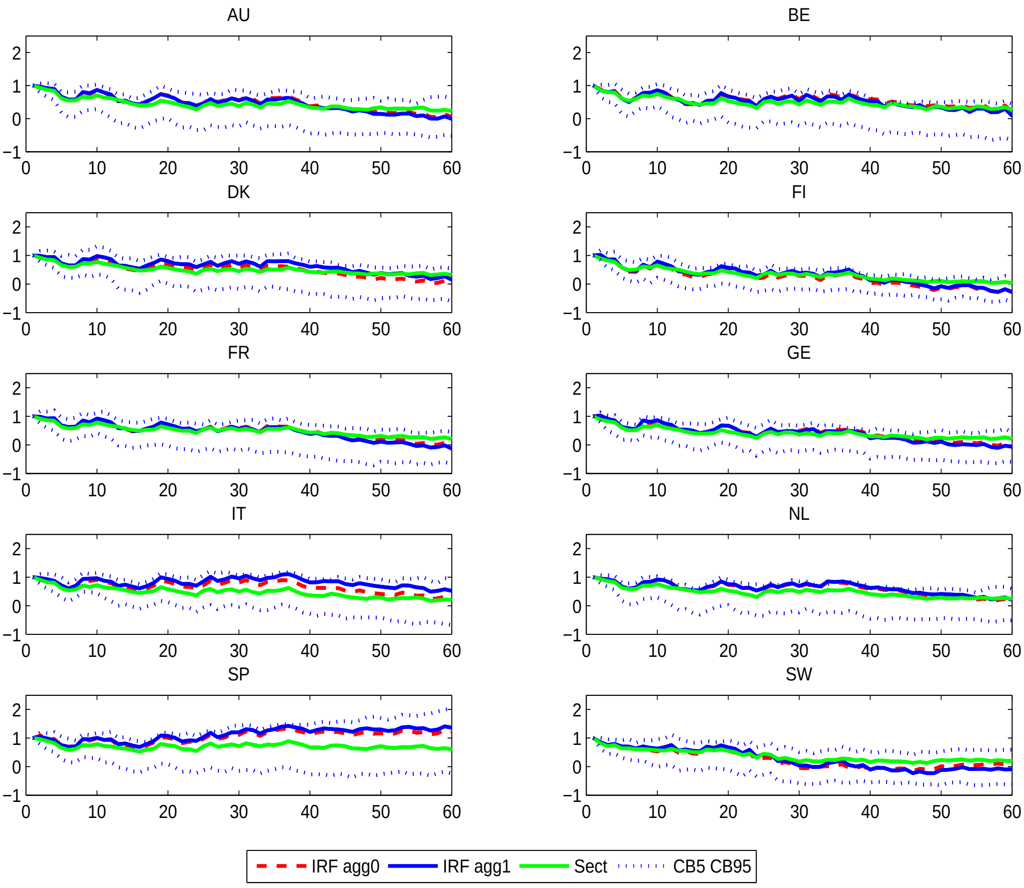

FIG 1. Aggregate IRFs estimated with aggregate and disaggregate data.

TABLE I

AGGREGATE VS. SECTORAL PERSISTENCE

		AU	BE	DK	FI	FR	GE	IT	NL	SP	SW
	Agg0	37.98	42.46	37.95	18.80	37.57	36.86	46.42	43.61	89.52	19.82
HL	Agg1	37.52	40.18	44.08	16.04	37.21	31.32	60.51	44.19	118.53	22.38
	Sect	36.57	37.26	37.33	12.02	37.61	18.33	36.99	37.32	73.14	20.06
	Agg0	15.82	9.07	9.82	8.16	9.83	9.40	10.00	9.87	11.74	8.27
CIR(12)	Agg1	16.01	9.05	10.41	8.64	10.00	9.53	10.35	9.91	10.92	8.87
	Sect	13.90	8.59	9.10	8.03	9.03	8.29	8.61	8.93	9.04	8.15
	Agg0	22.71	15.55	16.76	12.38	16.84	15.41	18.18	17.51	21.77	14.17
CIR(24)	Agg1	22.59	15.37	18.55	13.90	17.11	15.54	19.60	17.64	21.48	15.94
	Sect	18.99	14.30	15.28	12.54	15.52	13.24	14.68	14.80	16.43	14.28
	Agg0	29.09	23.45	23.89	15.78	23.95	21.48	27.98	26.14	35.25	15.10
CIR(36)	Agg1	27.91	23.04	27.42	18.50	23.96	21.28	31.19	26.56	35.94	17.88
	Sect	26.76	20.22	21.24	16.56	22.04	18.04	20.96	21.02	24.79	17.48
	Agg0	29.09	33.90	29.94	14.35	29.53	26.08	39.74	35.97	62.67	14.81
CIR(60)	Agg1	27.91	31.82	37.80	18.48	28.11	24.33	48.88	37.52	67.57	15.65
	Sect	26.76	29.14	30.61	19.75	30.23	24.66	28.38	28.88	29.65	22.39

4. THE DISTRIBUTION OF SECTORAL PERSISTENCE

The results obtained in the previous section motivate the remainder of our empirical analysis: since the persistence of the aggregate real exchange rate is a simple function of that of the sectoral ones, a lot of information about the sources of aggregate persistence can be obtained by analyzing sectoral exchange rates.

This section describes the distribution of sectoral persistence. We first document the high heterogeneity in sectoral RERs and show that the distribution is highly skewed to the right, that is, a few sectors are highly persistent while the rest are considerably less so.

Since aggregate response is the average of the individual responses, the former can be very much determined by the persistence of the sectors at the right tail of the distribution of persistence. We show that this is precisely what happens: the 30% most persistent sectors account for approximately 50% of the aggregate HL, on average, and this number reaches 70% for some countries in our dataset. Furthermore, the HL associated with the aggregate of the remaining 70% of sectors is, in general, smaller than two years, that is, well below the consensus view.

Thus, a careful examination of the characteristics of these sectors and what causes them to be so persistent can provide valuable insight into the forces that shape aggregate behavior. This section also provides a description of these sectors while Section 5 uses quantile regression to investigate the factors that can account for the persistence in the upper quantiles.

4.1. Heterogeneity in RER sectoral data

Many studies have documented the existence of a high degree of heterogeneity in sectoral RER data (see Imbs et al., 2005, Crucini and Shintani, 2008, for some recent references).

The dataset considered in this paper is not an exception. We have estimated the density functions of the CIR(h) at several horizons, namely, $h = \{36, 60, 84\}$ months, that is, the cumulative response to a shock after 3, 5 and 7 years, and the corresponding graphs are reported in Figure 2.[6] Two important characteristics stand out. Firstly, there is a considerable degree of heterogeneity in all the countries and it increases when further horizons are considered. The average across countries of the coefficient of variation is 0.4497, 0.7015 and 0.9243, for $h = \{36, 60, 84\}$ months, respectively. Secondly, the distributions are highly skewed to the right and, again, the further the horizon of the CIR considered, the higher the skewness. The average skewness of the CIR(h) is 0.781, 1.1779 and 1.8150 for $h = \{36, 60, 84\}$. Since persistence is a long-term property, the pattern of the densities of the different CIR indicates that persistence is highly asymmetric and heterogeneous and that these

[6] Densities have been estimated using the Epanechnikov kernel.

characteristics accentuate with the horizon considered.

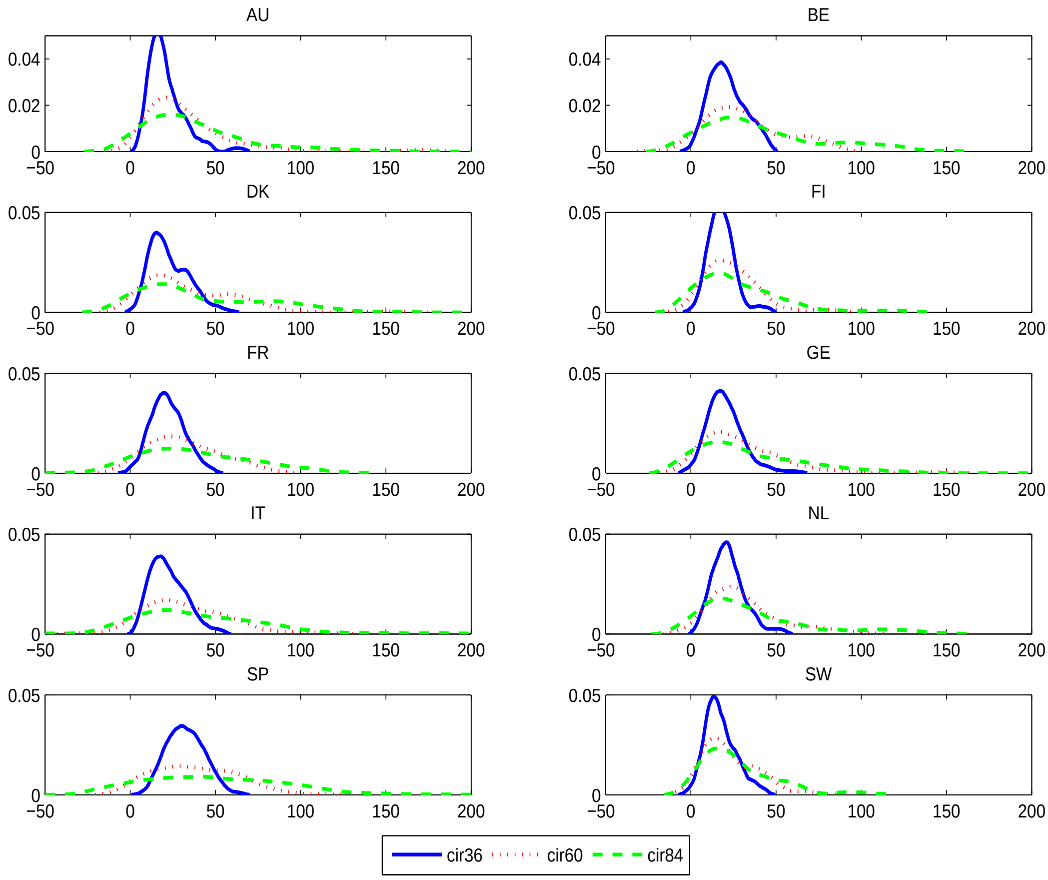

FIG 2. CIRs densities at different horizons

The fact that sectoral persistence is highly heterogeneous and asymmetric has important implications: since the aggregate IRF is just the average of the sectoral ones and averages are very non robust statistics, the aggregate IRF and its associated scalar measures are likely to be determined by a few, but highly influential, sectoral IRFs. That is, a reduced number of highly persistent sectors can be responsible for the high levels of persistence observed at the aggregate level.

In order to investigate this conjecture, all the sectors in country c have been ranked according to their degree of persistence, as measured by their individual HLs. Next, we have eliminated the top 10% most persistent sectors and have aggregated the remaining 90%.[7]

[7] The aggregate has been computed as the weighted average of the remaining sectors, where the weights

Finally, we have reestimated the IRF of this series using (7) following a similar procedure to the one described in Section 3. The same exercise has been repeated by excluding the 20% and the 30% most persistent sectors. Table II reports the HLs corresponding to the resulting processes. For convenience, the first column in this table reproduces the HL of the aggregate RER reported in Table I (second column). Columns 2 to 4 report similar figures computed by excluding the top 10, 20 and 30% most persistent sectors, respectively.

Table II shows that, when the top 30% most persistent sectors are excluded, the HL falls drastically: with the exception of Spain, all countries display HLs smaller than 2 years and the elimination of these sectors reduces the HL by 51%, on average. For some countries, such as Finland, Italy and Germany, the decrease is even more spectacular: their HL drops by 69%, 67% and 64%, respectively.

It follows that an analysis of the excluded sectors and of the causes that make them so persistent can be very informative about the sources of aggregate RER persistence. We now consider these issues.

TABLE II

HL eliminating the most persistent sectors

	HL, all sectors	HL, less 10% sectors	HL, less 20% sectors	HL, less 30% sectors
AU	37.52	37.24	20.28	18.73
BE	40.18	37.85	18.94	18.55
DK	44.08	38.13	20.64	19.78
FI	36.04	19.82	11.06	11.01
FR	37.21	36.61	25.11	23.98
GE	31.33	19.96	20.01	11.18
IT	60.51	55.07	20.38	20.01
NL	44.19	41.71	37.64	20.30
SP	118.53	118.51	99.58	53.11
SW	22.38	22.35	19.29	19.18

employed are those described in footnote 4 divided by their sum, so that the resulting new weights add up to 1.

4.2. Persistence by groups of sectors

To analyze the relation between persistence and sector characteristics, we have grouped the sectors into two long-established categories. The first one classifies them as food (F), durable (D), nondurable (ND), services (S) and energy (E). The second one, following the traditional dichotomy, as traded (T) and nontraded (NT).[8] The relation between the aggregate and the sectoral IRFs established in (8) allows us to quantify the contribution of each sector or group of sectors, to aggregate persistence. Thus, in this section, we compute their contribution to total persistence by type of sector. We also analyze the relative composition of the top 30% most persistent sectors.

To evaluate these contributions, we have proceeded as follows. The aggregate IRF, $IRF_{c,aggr}$, can be decomposed thus

$$IRF_{c,\ aggr}\left(t,h\right)=\sum_{j=1}^{J}\sum_{i=1}^{N_j}\omega_i IRF_{c,i}\left(t,h\right),$$

where J denotes the number of groups considered and N_j is the number of sectors in group j, with $\sum_{j=1}^{J}N_j=N$. The percentage contribution of group j to the aggregate IRF at horizon h, denoted as $C_{c,j}\left(h\right)$, can be computed as

$$C_{c,j}\left(h\right)=\frac{\sum_{i=1}^{N_j}\omega_i IRF_{c,i}\left(t,h\right)}{IRF_{c,aggr}\left(t,h\right)=\sum_{i=1}^{N}\omega_i IRF_{c,i}\left(t,h\right)}.$$

Thus, the percentage contribution of group j to the aggregate cumulative response, PC-CIR$_{c,j}\left(h\right)$, is defined as

$$\text{PC-CIR}_{c,j}\left(h\right)=\sum_{r=1}^{h}C_{c,j}\left(r\right), \tag{12}$$

The relative contribution of group j in country c to the HL, denoted as PC-HL$_{c,j}$, has been computed in the following way,

$$\text{PC-HL}_{c,j}=\frac{\sum_{i=1}^{N_j}\omega_i IRF_{c,i}\left(t,HL_c\right)}{\sum_{i=1}^{N}\omega_i IRF_{c,i}\left(t,HL_c\right)} \tag{13}$$

[8] Housing and services are considered as nontraded (with the exception of air travel and financial services) while all other sectors are considered as traded.

Table III presents the corresponding figures for the two categories considered. Columns 2 to 6 display the average across countries of the PC-CIR$_{c,j}$ (h) , for different values of h, and of the PC-HL$_{c,j}$, defined in (12) and (13) , respectively, for each of the groups considered. In addition, the first column presents the average across countries of the weights that Eurostat assigns to each of these categories in order to build the price index. For example, the average Eurostat weight (across countries) of all the products labelled as food is 24%. We include this column in order to be able to evaluate whether the percentage contribution to total persistence is larger or smaller than the percentage weight in aggregate RER.

It is possible to assess the evolution of the persistence of shocks over time across groups of sectors by looking at the different horizons of the CIR in columns 3 to 6. In the short run (one year), the impact of shocks in all groups is very similar, as shown by the fact that the contribution to CIR(12) of each group is almost equal to its corresponding initial weight. However, as farther horizons are analyzed, the picture changes substantially. Durable goods become the group with the highest contribution to long run persistence. They account for 43% of the total cumulative effect of shocks in the long-term (CIR(84)). Moreover, their contribution to the cumulative response relative to the initial weight of the group increases substantially as farther horizons are considered. For instance, the contribution to CIR(60) (38%) and CIR(84) (43%) exceeds their corresponding initial weight (27%) by 41% and 59%, respectively. Within this group, the *electronic products* and the *clothing and personal effects* subcategories are the most persistent components. Their long-run contribution to the CIR exceeds their initial weights by 100% and 80%, respectively. On the other hand, the contribution of the services and energy sectors to aggregate persistence decreases when distant horizons are considered. Their contribution to ($CIR(60)$, $CIR(84)$) is only (60%, 50%) and (76%, 61%) that of their initial weight, for energy and services, respectively. This result is quite surprising because services are usually believed to be behind the high persistence of aggregate RER. It is also remarkable that the contribution of food and non durables remains fairly constant over time and very similar to its initial weight.

The traded/non traded good categories also displays a clear pattern: the percentage contribution of the traded goods category to total persistence is bigger than its initial weight and increases with the horizon considered. For instance, the contribution to long-run persistence, as measured by CIR(60) and CIR(84), exceeds its initial weight by 14% and 20%, respectively. So, the non traded category seems to be less persistent than the traded one, as shown by the fact that its contribution to CIR(60) and CIR(84) is only 0.76% and 0.68% its initial weight. Nevertheless, the discrepancies between the traded and nontraded groups appear to be considerably smaller than those obtained with the first classification described above, suggesting that the characteristics of these groups of goods might not be that different, as has been pointed out by other authors (see Engel, 1999, Chari et al., 2002, Crucini and Shintani, 2008).

TABLE III

Aggregate persistence by group of sectors (in % terms)

	Weights	PC-HL	PC-CIR(12)	PC-CIR(36)	PC-CIR(60)	PC-CIR(84)
1. FOOD	0.23	0.23	0.26	0.24	0.23	0.21
- Food	0.18	0.17	0.20	0.19	0.18	0.17
- Alcohol and Tobacco	0.05	0.05	0.06	0.05	0.05	0.05
2. ENERGY	0.10	0.06	0.09	0.08	0.06	0.05
3. NON DURABLES	0.06	0.08	0.06	0.07	0.08	0.08
4. DURABLES	0.27	0.41	0.25	0.31	0.38	0.43
- Clothing and personal effects	0.10	0.19	0.10	0.13	0.16	0.18
- Durables for the dwelling	0.06	0.08	0.05	0.06	0.08	0.09
- Motor vehicles	0.07	0.09	0.07	0.08	0.09	0.10
- Electronic products	0.02	0.03	0.02	0.02	0.03	0.04
- Recreational and cultural	0.02	0.02	0.01	0.02	0.02	0.02
5. SERVICES	0.34	0.23	0.34	0.29	0.26	0.21
- Services relating to the dwelling	0.10	0.07	0.09	0.09	0.07	0.06
- Transport	0.05	0.03	0.04	0.04	0.03	0.03
- Financial services	0.01	0.03	0.02	0.02	0.03	0.03
- Recreational and cultural services	0.15	0.08	0.16	0.12	0.11	0.09
- Other services	0.02	0.02	0.02	0.02	0.02	0.00
TOTAL	1	1	1	1	1	1
TRADED	0.62	0.74	0.61	0.66	0.71	0.74
NON-TRADED	0.38	0.26	0.39	0.34	0.29	0.26
TOTAL	1	1	1	1	1	1

Summarizing, it seems that persistence is dominated by sectors in the durable category. If this is true, the durable group should be overrepresented in the right tail of the distribution with respect to the whole sample. To investigate this issue further, we have analyzed the relative composition of the 30% most persistent sectors obtained in the previous section. The following simple exercise has been carried out. For each country, we have computed the weight of each of the groups considered above within the 30% most persistent sectors. In order to do that, we have simply added the relative weights assigned by Eurostat to the sectors in a particular category and have divided these figures by their sum so that the resulting weights add up to 1. Next, we have subtracted the weight that the corresponding category has in the whole sample. Figures 3 and 4 display the results for the two categories of sectors considered above. Large and positive (negative) bars suggest that the relative weight of the corresponding group is large (small) among the most persistent sectors and, therefore, this group is overrepresented (underrepresented) in the upper quantiles of the distribution of persistence. On the other hand, bars that are close to zero imply that the distribution of these sectors in the upper quantiles does not differ much from that observed in the unconditional distribution.

On average, sectors in the food, energy and non durable categories are equally represented in the upper quantiles and in the overall distribution, as shown by the short bars associated with these groups. Durable goods and services, however, are over and underrepresented, respectively, in the right tail of the distribution. On average, the weight of the durable goods category in the upper quantiles exceeds its unconditional weight by 35%. Moreover, the correlation between these figures and the country HLs (first column in Table II) is 72%, suggesting a strong link between the persistence of the durable component and aggregate RER persistent. It follows that the more overrepresented durables are among the most persistent sectors in country c, the more persistent the corresponding aggregate RER. This relation is very significant.

The opposite is found for the service category: its weight in the upper quantiles is 25% smaller than its corresponding unconditional weight. Accordingly, it is not surprising to see that it is the traded category, and not the nontraded one, which is overrepresented among the most persistent sectors, as opposed to what traditional theories would suggest. The weight of the traded category exceeds its unconditional weight by almost 20%, on average.

The results in this section imply that traditional theories based on the traded/nontraded dichotomy will fail to account for the persistence observed in European exchange rates. Aggregate persistence seems to be driven by the persistence of sectors that can be highly tradable, as goods in the durable group are. In the following section we carry out a more formal investigation using quantile regression analysis to determine the factors that can account for the observed levels of persistence.

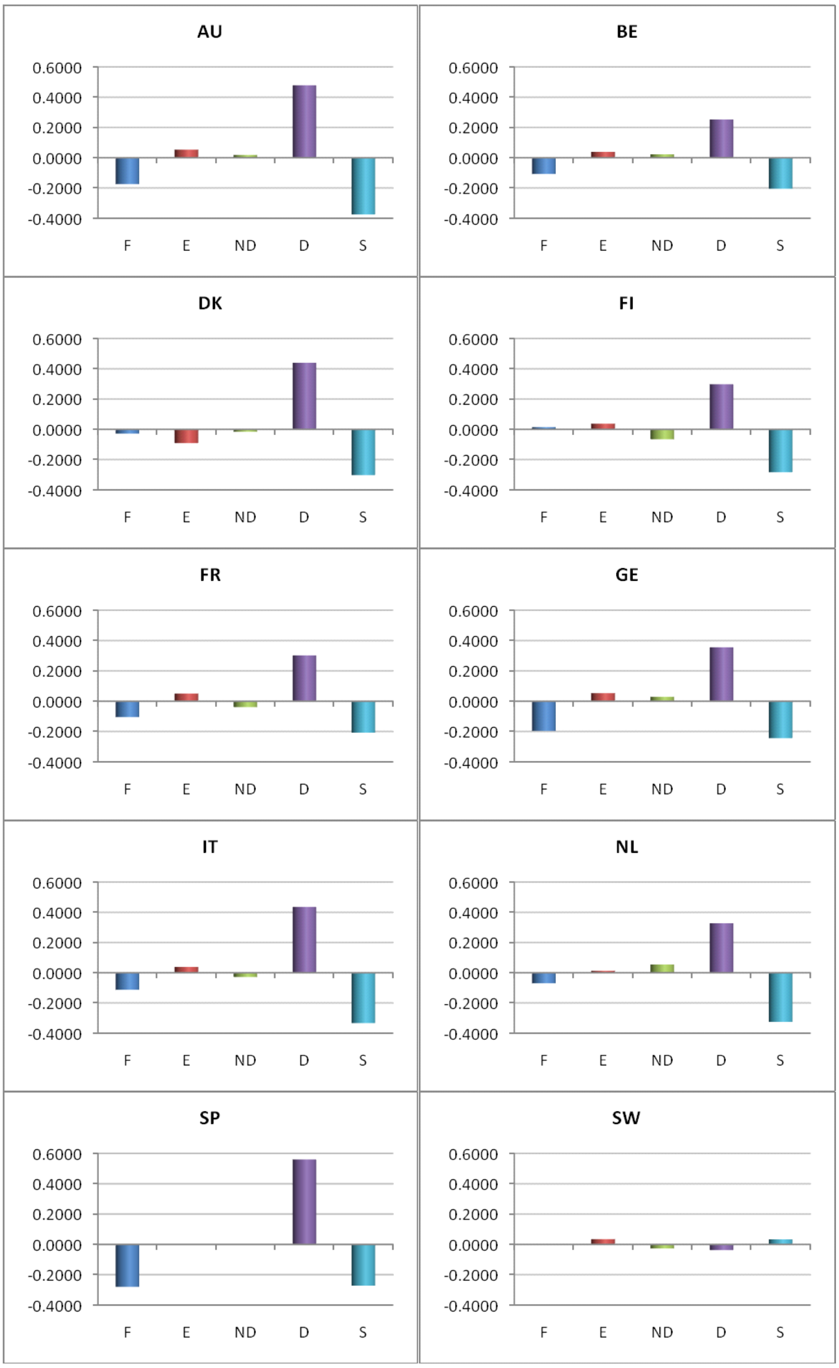

FIG 3. Relative composition of the 30% most persistent sectors

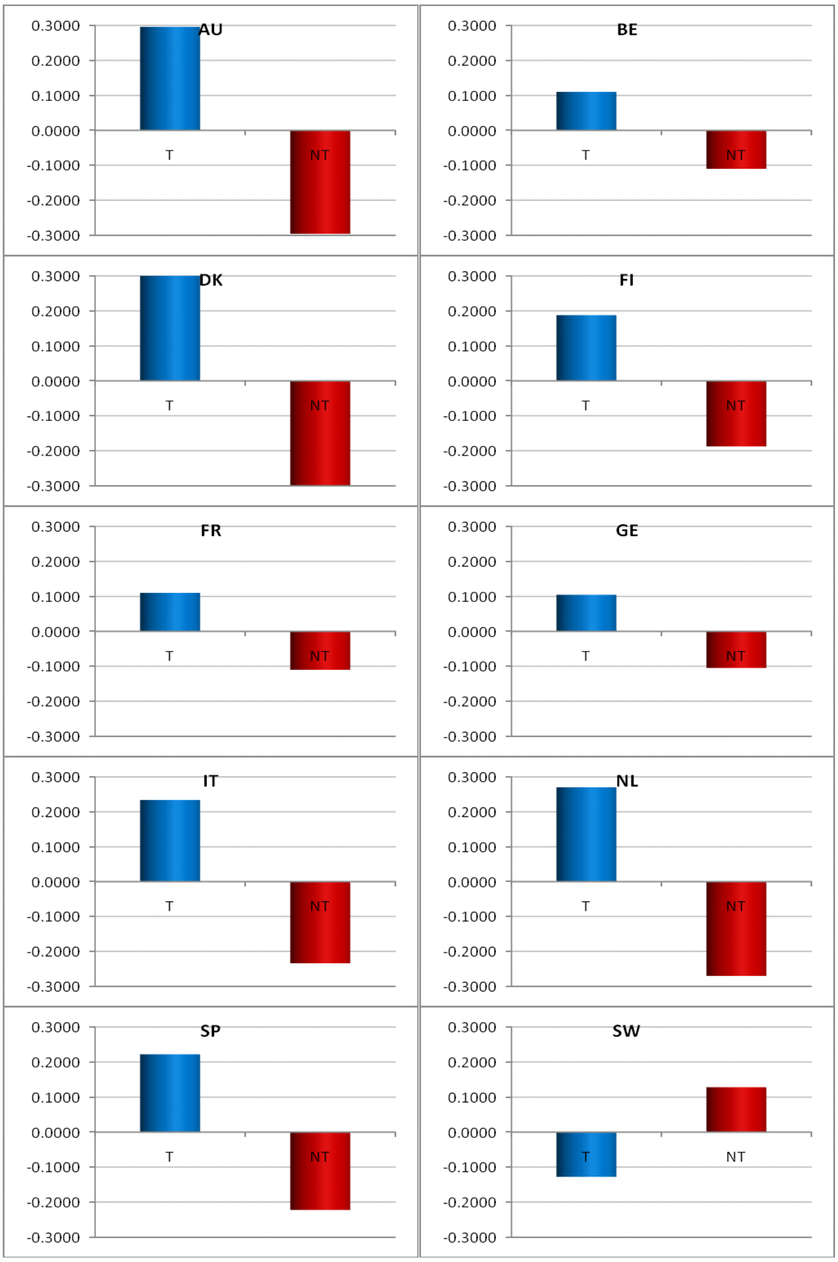

FIG 4. Relative composition of the 30% most persistent sectors

5. ACCOUNTING FOR RER PERSISTENCE

Explanations of the slow convergence to PPP have been traditionally related to one (or several) of the following theories: barriers to trade, such as tariffs or transportation costs, that can be high enough to prevent some goods and services from being traded and, therefore, arbitraged; imperfect competition practices such as pricing to market (PTM), combined with price stickiness that are able to create a wedge between the prices of the same good sold in different markets, violating the Law of one Price (LOP) which is a building block of PPP; and different consumption preferences across countries that mean that inflation measurements are computed on different consumption baskets, so there is no reason for exchange rate changes to offset official measures of inflation differences.

The goal of this section is to investigate empirically whether these theories can account for the persistence observed in European RERs. In doing so, we will pay particular attention to explaining the behavior of the most persistent sectors since, as shown in the previous section, they are crucial to understanding the behavior of the aggregate RER.

By concentrating on harmonized sectoral price data, we can discard the third explanation as a source of deviations from PPP, since we consider disaggregate prices referring to a homogeneous basket of goods. Thus, in the following, we concentrate on the first two potential explanations: the existence of goods in the consumption basket that are nontraded and the lack of perfect competition combined with price stickiness in goods markets.

The conventional approach emphasizes the fact that many goods in the consumption basket are not traded (Salter, 1959 and Swan, 1960). Since the forces of arbitrage are, at best, weak on these goods, volatile and persistent aggregate RERs are to be expected. However, the empirical support for this theory is mixed. Engel (1999) suggests decomposing the RER into two components: one due to changes in two countries' relative prices of nontradable to tradable goods and the other due to changes in the countries' relative price of tradables. Under the classical theory, the second term obeys the LOP so, all the movements in RER are due to movements in the first component. However, Engel (1999) finds that the opposite is true: nearly all the variability of the RER can be attributed to the second component. Similar findings have also been reported by Chari et al. (2002). Using a micro panel of local currency prices of individual retail goods and services in major cities, Crucini and Shintani (2008) have found that the median HL of nontraded goods is higher than that corresponding to traded goods, although the difference is very small (2 to 6 months, depending on the geographical area considered).

In response to this mixed evidence, a new theory that combines pricing-to-market (PTM) behavior and nominal rigidities has emerged to account for the little effect of exchange rate movements on traded goods prices. Betts and Devereux (1996) made the initial contribution along these lines by augmenting the framework introduced by Obstfeld and Rogoff (1995) to allow for PTM. Bergin and Feenstra (2001) incorporate preferences that exhibit the property that the elasticity of demand is not constant. They show that this property is important to allow for PTM and staggered contracts to generate endogenous persistence. In their model, a fraction ϕ of the goods are nontraded internationally and they emphasize that a lower degree of openness increases persistence. The intuition of this result is that, under a home currency depreciation, home producers will tend to lower the price they charge abroad. If home goods play a large role in the foreign consumption basket, then the foreign price index will go down, offsetting the impact of the depreciation of home currency on the real exchange rate. Nevertheless, the model is not able to reproduce the high persistence levels observed in the data.

Also in the spirit of Obstfeld and Rogoff (1995), Chari et al. (2002) consider a model where all goods can be traded and where PTM and staggered contracts occur at the intermediate goods level. This model is successful in replicating the volatility observed in RER data but it cannot match the degree of persistence observed in RER data unless implausible parameter values are assumed at the outset. By introducing heterogeneity in price stickiness across sectors, Carvalho and Nechio (2008) are able to match the observed RER persistence in a model which, otherwise, presents similar features to Chari et al. (2002)'s.

Hairault and Sopraseuth (2003) provide an integrated model with PTM and non tradables and show that both effects are deeply intertwined but their model suggests that PTM is more important than non tradables in accounting for RER volatility. See also Faruqee (1995), Chang and Devereux (1999) and Devereux and Engel (1998) for related references.

In the following, we empirically identify the main determinants of the persistence observed in European RERs. More specifically, we analyze whether the widespread presence of nontraded goods in the consumption basket (or in the inputs used in the elaboration of the final good), the prevalence of PTM and nominal rigidities, either at the final and the intermediate goods level, or a combination of both factors can account for the slow reversion to parity of European relative prices. Our analysis primarily focuses on analyzing the behavior of the upper quantiles of the distribution since, as shown in the previous section, they shape, to a large extent, the persistence observed at the aggregate level. We also explore how the explanatory power of the different variables considered to account for RER persistence change at different horizons of the evolution of the shock.

We now introduce the set of dependent and independent variables used to test the theories above, the econometric techniques employed in our empirical exercise and the results obtained.

5.1. Independent and dependent variables

The explanatory variables considered belong to three categories: those that are a proxy for market structure and imperfect competition, those that try to measure the degree of openness of the sectors and some control variables. To elaborate these variables, three additional databases have been employed: the United Nations Commodity Trade Statistic Database (UN Comtrade), the OECD Structural Analysis Statistics (STAN, 2008 edition) and the Input-Output Tables (IOT) from the OECD. Additional details on the construction the regressors are provided in Appendix 1.

Variables related to market structure.

Intra-Industry Trade (IIT). As emphasized by Faruqee (1995), under PTM, the persistence of the real exchange rate increases as the elasticity of substitution between home and foreign varieties increases. The intuition is clear: as the elasticity of substitution rises, the domestic monopolistically competitive exporting firms have to maintain their prices more in line with those of the foreign firms, thus increasing price rigidities in local currency terms. Since domestic and foreign products are more substitutable under intra-industry trade, ceteris paribus, a greater degree of intra-industry trade leads to more persistent exchange rates.

We follow Grubel and Lloyd (1975) and define the IIT index for sector i in country c as

$$IIT_{t,i}^{c} = 1 - \frac{\sum_{i=1}^{N} \left| X_{t,i}^{c} - M_{t,i}^{c} \right|}{\sum_{i=1}^{N} (X_{t,i}^{c} + M_{t,i}^{c})}, \tag{14}$$

where $X_{t,i}^{c}$ ($M_{t,i}^{c}$) represents total exports (imports) of sector i in country c.

As shown by Chari et al. (2002), the existence of PTM at the intermediate goods level can also have a big impact on the persistence of the relative price of the final good i even when it is sold in a perfectly competitive market. To capture this effect, we have also computed an index that measures the degree of IIT associated with the intermediate items needed to produce good i. To do this, we have calculated the weighted average of IIT indices (where each of them is defined as in (14)) for each of the inputs employed in the elaboration of good i, where the weights are the relative contribution of the corresponding input g to the production of good i, as stated by the Input-Output tables of country c. Thus, the intermediate goods IIT index (denoted as Input-IIT), is computed as

$$\textit{Input-}IIT_{t,i}^{c} = \sum_{g=1}^{G} \omega_g IIT_{t,g}^{c}$$

where ω_g and G denote the share of good g and the total number of inputs involved in the production of good i, respectively, and $IIT_{t,g}^{c}$ is computed as in (14).

Price-cost margin (PCM). Imperfect competition will typically involve market segmentation and price discrimination across the destination markets (Goldberg and Knetter, 1997). A classical measure of imperfect competition is the price-cost margin variable, that approximates the degree of profitability of an industry. Thus, the lower the value of the PCM, the fiercer the competition in this sector. The PCM relative to sector i in country c is given by

$$PCM_{t,i}^{c} = \frac{VA_{t,i}^{c} - W_{t,i}^{c}}{VA_{t,i}^{c} + CM_{t,i}^{c}}, \tag{15}$$

where $VA_{t,i}^{c}$ is the total value added of sector i (the value of total production minus the cost of materials) in country c, $W_{t,i}^{c}$ is labor compensation and CM_{ci} denotes the cost of materials. We have also computed the PCM associated with the inputs employed in the production of good i in a similar fashion as $\textit{Input-}IIT_{t,i}^{c}$. It is defined as

$$Input\text{-}PCM_{t,i}^{c} = \sum_{g=1}^{G} \omega_g PCM_{t,g}^{c},$$

where $PCM_{t,g}^{c}$ is the price-cost margin of input g defined as in (15).

Price Stickiness. It has also been emphasized that, without price stickiness, a model of PTM cannot generate adequate persistence (Chang and Devereux, 1998). To proxy price stickiness, we have considered the volatility of sectoral inflation (VOL). If the prices of sector i are very sticky, low levels of sectoral inflation volatility will be expected and viceversa. We compute the volatility of inflation for sector i in country c as

$$VOL_i^c = std(INFL_{t,i}^c),$$

where *std* denotes standard deviation and $\mathrm{INFL}_{t,i}^{c}$ is the inflation rate of sector i in country c, defined as

$$INFL_{t,i}^{c} = 1200\left(p_{c,i,t} - p_{c,i,t-1}\right) \tag{16}$$

Variables related to the tradability of goods.

Openness. Conventional wisdom suggests that the more traded goods are, the more important the forces of arbitrage are and, therefore, the degree of openness should have a negative impact on RER persistence. In a different setup, Bergin and Feenstra (2001) and Faruqee (1995) emphasize that, under PTM and nominal rigidities, an increase in openness fosters price adjustment when changes in the exchange rate take place, offsetting the impact of exchange rate movements and thus reducing RER persistence.

The degree of openness of sector i is measured as

$$OP_{t,i}^{c} = \frac{X_{t,i}^{c} + M_{t,i}^{c}}{GDP_{t,i}^{c}}. \tag{17}$$

where $\mathrm{GDP}_{t,i}^{c}$ is total GDP of sector i in country c at time t.

As for the group of variables related to market structure, we have also computed the degree of openness of the intermediate inputs, defined as

$$Input\text{-}OP_{t,i}^{c} = \sum_{g=1}^{G} \omega_g OP_{t,g}^{c},$$

where $OP_{t,g}^{c}$ denotes the degree of openness of the intermediate good g, computed as in (17).[9]

Control variables

Finally, we have also controlled for another set of variables that may have an impact on RER persistence.

Inflation. It has been argued that a higher inflation rate can lead to a more rapid price adjustment (Ball and Mankiw, 1994) and, thus, to a lower degree of nominal rigidities. Some studies have shown that PPP tends to hold well for high inflation countries (McNown and Wallace, 1989) and that a higher level of inflation is associated with a lower level of real exchange rate persistence (Cheung and Lai, 2000). To control for the level of inflation, we have considered the variable $\text{INFL}_{t,i}^{c}$, defined in (16), that measures the inflation in sector i of country c.

Following previous studies, we also considered other control variables, such as government spending and the volatility of the exchange rate (see Cheung et al, 2001). However, these variables were not significant and did not seem to have any important impact on the coefficients of the remaining variables so, for the sake of brevity, we do not report the estimation output corresponding to models containing these variables.

Dependent variables

Our main dependent variable is the sectoral CIRs defined as

$$CIR_{c,i}(h) = \sum_{l=0}^{h} IRF_{c,i}(t,l), \text{ for } i = 1, ..., N.$$

To capture the explanatory power of the independent variables at different moments of the lifetime of the shocks, several values of h have been considered, namely, $h = \{12, 36, 60, 84\}$, in order to measure the short (h=12), medium ($h = 36$) and long-run ($h = \{60, 84\}$) effect of shocks. For completeness, sectoral HLs have also been considered as the dependent variable.

[9] We also tried other approaches to measure the degree of openness of the final and the intermediate goods. To account for transportation costs, we have considered two additional variables: *Distance,* proxied as the distance between national capitals; and *Trade Barriers*, computed as in Anderson and Wincoop (2003) and Novy (2008). However, none of these variables turned out to be significant or had any impact on the coefficients of the other variables so we decided to drop them from the analysis.

5.2. Econometric methods

In order to examine the empirical relations between RER persistence and the various theories outlined above, we have carried out both a standard and a quantile panel regression analysis. Standard regression methods only provide a single summary measure for the conditional distribution of the dependent variable (the conditional mean) given the predictors. However, it has been recognized that the corresponding estimates are not necessary indicative of the response of the dependent variable to the regressors on other parts of the conditional distribution. Since we are particularly interested in explaining the behavior of the most persistent sectors, the use of quantile regression techniques will provide us with a more complete picture of the covariate effects at the right tail of the distribution of RER persistence.

Following Koenker (2004), we consider the following model for the conditional quantile τ associated with the response of the corresponding persistence measure in sector i of country c :

$$Q_{y_{c,i}}\left(\tau|x_{c,i}\right) = \alpha_i + x_{c,i}'\beta\left(\tau\right);\ i = 1, ..., N; c = 1, ..., C, \tag{18}$$

where $(y_{c,i},\, x_{c,i})$ denote the values of the dependent and independent variables, respectively. The role of the $\alpha's$ is to control for individual unobserved heterogeneity that has not been adequately captured by other regressors in the model. However, α is assumed to be the same for all the quantiles and thus, it it is not allowed to depend on τ. This is because the number of observations in each sector is small and, therefore, it would be unrealistic to try to estimate a $\tau - dependent$ individual effect. Thus, α captures an individual specific location-shift effect. On the other hand, the effect of the regressors on $y_{c,i}$, $\beta\left(\tau\right)$, is allowed to depend on τ but it is assumed to be the same across sectors and countries. Since, in general, $x_{c,i}$ will contain an intercept, the estimated constant term will the sum of two components, one depending on τ but not on i and the other depending only on i.

Koenker (2004) suggests estimating model (18) for several quantiles simultaneously by solving

$$\min_{(\alpha,\beta)} V_p = \min_{(\alpha,\beta)} \sum_{\kappa=1}^{q} \sum_{c=1}^{C} \sum_{i=1}^{N} \omega_\kappa \rho_{\tau_\kappa} \left(y_{c,i} - \alpha_i - x'_{c,i} \beta \left(\tau_\kappa \right) \right) + \lambda \sum_{i=1}^{n} \left| \alpha_i \right|, \text{ for some } \lambda \geq 0, \quad (19)$$

where $\rho_\tau (e) = (\tau - I (e < 0)) e$, $I (.)$ is the indicator function and ω_κ is the relative weight given to the τ_κ quantile. These weights control the influence of the estimation of the individual effects on the quantiles. The term $\lambda \sum_{i=1}^{n} |\alpha_i|$ introduces a shrinkage of the $\hat{\alpha}'s$ to a common value. The intuition of this term is the following. When N is large relative to C, the estimation of a large number of individual effects α_i can bring about an important increase in the variance of all the estimates. By shrinking the unconstrained $\hat{\alpha}'s$ it is possible to improve the performance of both the individual fixed-effect estimates and the estimates of β. The parameter λ controls the degree of this shrinkage. For $\lambda = 0$, we have the fixed effect estimator while for $\lambda > 0$, we have the penalized estimator with fixed effects.

We have estimated model (18) by solving equation (19) for all the deciles, that is, $\tau_\kappa = \{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9\}$. To do so, we have assigned the same weight to each of the quantiles. As noticed by Koenker (2004), the appropriate choice of the shrinkage parameter λ remains to be investigated in this setup.[10] In order to check the robustness of our results, we have considered different values for λ=$\{$0.01, 0.1, 0.5, 1$\}$ and the results remained quantitatively very similar and qualitatively identical.

To evaluate the goodness of fit of our model we have followed Koenker and Machado (1999) who have introduced a goodness of fit measure for cross-sectional quantile regression analogous to the conventional R^2 statistic of a least squares regression. To do this, they consider a linear model for the conditional quantile function

$$Q_{y_i} (\tau) = x'_{1i} \beta_1 (\tau) + x'_{2i} \beta_2 (\tau),$$

and denote as $\hat{\beta} (\tau)$ the minimizer of $\hat{V}_c (\tau) = \min_{b_1, b_2} \rho_\tau (y_i - x'_{1i} b_1 (\tau) - x'_{2i} b_2 (\tau))$ and $\tilde{\beta} (\tau)$ the minimizer of the constrained problem $\tilde{V}_c (\tau) = \min_{b_1} \rho_\tau (y_i - x'_{1i} b_1 (\tau))$, where

[10] Lamarché (2006) examines the optimal choice of λ in a similar setting to the one considered in this paper but where both N and C are allowed to go to infinity. Since the value of C in our case is quite small, his results are not directly applicable to our problem.

$\rho_\tau(e)$ is defined as above. One can define a goodness of fit criterion as

$$R^* = 1 - \widehat{V}/\widetilde{V}.$$

In the panel quantile regression case, one can partition model (18) as

$$Q_{y_{c,i}}(\tau|x_{c,i}) = \alpha_i + x'_{1c,i}\beta_1(\tau) + x'_{2c,i}\beta_2(\tau),$$

and, calling $(\hat{\alpha}, \hat{\beta}_1(\tau), \hat{\beta}_2(\tau))$ the minimizer of $\hat{V}_p(\tau) = \min_{a,b_1,b_2} \rho_\tau\left(y_{c,i} - a_i + x'_{1c,i}b_1(\tau) + x'_{2c,i}b_2(\tau)\right)$ and $\tilde{\beta}(\tau)$ the minimizer of the constrained problem $\tilde{V}_p(\tau) = \min_{b_1} \rho_\tau\left(y_{c,i} - x'_{1c,i}b_1(\tau)\right)$, a goodness of fit measure for the estimation of all quantiles can be defined as

$$R^*_G = 1 - \widehat{V_p}/\widetilde{V_p},$$

Restricting the constrained model to contain only an intercept yields the goodness of fit measure considered in this paper.

Finally, a goodness of fit measure for each of the conditional quantiles can be computed as follows

$$R^*_{\tau_\kappa} = 1 - \widehat{V}_{\tau_\kappa}/\widetilde{V_{\tau_\kappa}}$$

where $\widehat{V}_{\tau_\kappa} = \sum_{j=1}^{M}\sum_{i=1}^{N} \rho_{\tau_\kappa}\left(y_{ij} - \hat{\alpha}_i - x'_{ij}\hat{\beta}(\tau_\kappa)\right)$ and $\widehat{\widetilde{V}}_{\tau_\kappa} = \sum_{j=1}^{M}\sum_{i=1}^{N} \rho_{\tau_\kappa}\left(y_{ij} - x'_{1ij}\tilde{\beta}(\tau_\kappa)\right)$.

With respect to the standard panel regression analysis, the following model has been considered

$$y_{c,i} = \theta_c + x'_{c,i}\beta + u_{c,i},$$

where the parameters have been estimated using the fixed-effects estimator, as the Hausmann test rejected the hypothesis of consistency of the random effects estimator.

5.3. Results

Two models have been estimated: Md 1 includes all the regressors described in Section 5.1 while Md 2 only contains those variables that turned out to be significant in Md 1. We have estimated conditional quantile regressions for all the deciles although, for the sake of brevity, full regression results are only presented for the quantiles $\tau_\kappa = \{0.5,\ 0.7,\ 0.9\}$.[11] Similar models have also been estimated using standard panel techniques. Tables IVa and IVb report the corresponding figures while Figure 5 displays the evolution of the estimated coefficients over the different quantiles considered. Finally, Table V reports the goodness of fit statistics defined in the previous section corresponding to Md 1.

The main results can be summarized as follows. The most important group of variables to account for RER persistence appear to be those related with the market structure of the inputs. In particular, the IIT variable associated with the intermediate goods (Input-IIT) has the expected positive sign and is always significant at the 5% significance level in all the models considered. Input-*PCM* also shows a positive relation with sectoral RER persistence that is generally significant, especially in the medium and long run and when higher quantiles are considered. As Figure 5 shows, the coefficients associated with these variables tend to be larger, the farther the horizon of the CIR considered and the higher the quantile.

Interestingly, once we have controlled for the market structure of the intermediate inputs, the market structure of the final good turns out not to be important in explaining RER persistence. In general, both IIT and PCM usually have the expected positive signs but they are not significant.

In line with the theoretical predictions, we find that a high degree of price stickiness is associated with a higher degree of persistence, as captured by the negative sign of the variable VOL, that is highly significant in all models.[12] Interestingly, the coefficients of the quantile regression parameters turn out to be considerably larger in absolute value as farther horizons and higher quantiles are considered.

With respect to the variables that capture the degree of tradability, *openness* appears, in general, with the expected negative sign for the quantiles to the right of the median although its sign is positive to the left of this value. The variable that captures the degree

[11] Results corresponding to the other quantiles are available upon request.

[12] A variable capturing the volatility of inflation of the intermediate inputs was also introduced in the regressions but it did not turn out to be significant.

of tradability of the inputs, *input-op*, usually presents a positive sign, especially in the upper quantiles, suggesting a positive relation between the degree of openness of the inputs and RER persistence. This result is not as surprising as it might look at first glance: internationally traded inputs are more exposed to PTM practices and, as seen before, this is the most important determinant of RER persistence. Nevertheless, neither OP nor Input-OP are significant in any of the models considered. The lack of significance of these variables confirms recent findings that suggest that traded and nontraded goods have similar characteristics (Engel, 1999 and Chari et al., 2002) and, therefore, this distinction is not key in accounting for persistence. Another aspect that can have a role in explaining the lack of significance of these variables is that CPI data, even at the very disaggregate level considered in this paper, does not allow us to completely disentangle traded and nontraded goods because the price of traded goods often involves nontraded components, such as marketing and distribution services. In addition, Europe is an area where trade barriers are very low since tariffs have been eliminated and trade costs are relatively small and, therefore, one could expect that the traded/non traded categories are less important than in other geographical areas.

Finally, inflation has a positive impact on RER persistence. This result suggests that, once price variability has been taken into account, a higher level of inflation is related to higher persistence levels. This result is not surprising since, in general, high inflation countries such as Spain or Italy are usually those presenting the highest persistence levels.

The results of the standard panel regression are very much in line with the discussion above: the variables associated with the market structure of the inputs and with the price stickiness of the final good are always significant and present the expected sign. However, the market structure of the final good, as well as its degree of tradability, do not appear to be important to account for the persistence of shocks to sectoral RERs.

Although the values of the coefficients from the quantile regressions and standard panel regressions can be quite different, the confidence bands of the latter usually include the estimated quantile coefficients (with some exceptions for Input-IIT, INFL and VOL). This is probably due to the fact that panel coefficients have been estimated using only a small number of countries and, therefore, these estimates present, in general, large standard deviations.

Finally, in spite of their simplicity, the models considered in this section are able to explain an important proportion of the variability of the different dependent variables (around 65% and 45% for the panel and quantile regressions, respectively), as shown in Table V.

Summarizing, our results are in agreement with theoretical models such as Chari et al. (2002) and Carvalho and Nechio (2008). PTM at the intermediate goods level and price stickiness seem to be key determinants of RER persistence. The classical dichotomy that classifies goods into traded and non traded appears not to account for European RER persistence.

TABLE IVa

QUANTILE REGRESSION RESULTS (I)

	τ_κ	CIR, Short run		CIR, Medium Run		CIR, Long run				HL	
		CIR(12)		CIR(36)		CIR(60)		CIR(84)			
		Md. 1	Md. 2	Md 1	Md 2	Md 1	Md 2	Md 1	Md 2	Md 1	Md 2
OP	0.5	-0.02	-	-0.10	-	0.12	-	-0.29	-	0.49	-
	0.7	-0.00	-	-1.05	-	-1.71	-	-0.70	-	-0.78	-
	0.9	-0.11	-	-1.13	-	-1.96	-	-2.59	-	-1.74	-
	panel	0.00	-	-0.08	-	0.15	-	0.06	-	0.45	-
Inputs-OP	0.5	0.23	-	0.92	-	-0.08	-	-0.48	-	2.11	-
	0.7	0.20	-	1.64	-	1.14	-	0.12	-	3.51	-
	0.9	0.94	-	15.73	-	22.61	-	6.62	-	-5.38	-
	panel	1.66	-	5.57	-	7.13	-	9.15	-	-17.85	-

Notes: *, ** denote significance at the 10 and 5% level, respectively.

TABLE IVb

Quantile Regression Results (II)

		CIR, Short run		CIR, Medium Run		CIR, Long run				HL	
		CIR(12)		CIR(36)		CIR(60)		CIR(84)			
	τ	Md 1	Md 2	Md 1	Md 2	Md 1	Md 2	Md 1	Md 2	Md 1	Md 2
IIT	0.5	0.52	-	1.37	-	1.14	-	2.18	-	-2.83	-
	0.7	0.45	-	0.86	-	0.76	-	0.02	-	-4.99	-
	0.9	0.71	-	1.69	-	3.94	-	-0.71	-	-28.43	-
	panel	0.33	-	-0.02	-	0.52	-	1.26	-	-6.29	-
Input -IIT	0.5	1.43**	1.40**	8.89**	8.83**	15.04**	15.41**	16.39**	17.56**	25.41**	22.41**
	0.7	0.97**	1.33**	8.60**	9.90**	20.10**	24.35**	26.56**	26.07**	31.77**	31.88**
	0.9	1.73*	1.53**	10.27**	9.06**	26.22**	27.13**	53.52**	50.90**	72.01**	55.60**
	panel	1.83**	1.66**	10.54**	9.90**	18.85**	18.96**	24.00**	24.04**	39.13**	35.53**
PCM	0.5	1.49	-	5.81	-	2.09	-	-7.97	-	-30.66**	-
	0.7	0.88	-	2.92	-	-2.82	-	-5.09	-	-37.32*	-
	0.9	0.94	-	15.73	-	22.61	-	6.62	-	-5.38	-
	panel	1.66	-	5.57	-	7.13	-	9.15	-	-17.85	-
Input -PCM	0.5	3.81*	4.34	18.01*	19.83*	25.15	28.59	35.00	29.41	87.16**	52.08**
	0.7	4.52*	5.13**	24.76**	23.08**	51.54**	60.86**	33.64*	33.33*	127.23**	107.13**
	0.9	11.04**	10.02**	256.57	34.12*	49.90	61.24**	89.26*	77.24*	201.00	308.75**
	panel	3.96*	4.53**	18.65*	21.82**	45.21*	49.02**	66.38*	74.22**	108.72**	105.67**
VOL	0.5	-0.39**	-0.38**	-1.15**	-1.12**	-1.24**	-1.39**	-1.51**	-1.52**	-1.04**	-1.02**
	0.7	-0.37**	-0.34**	-1.16**	-1.14**	-1.70**	-1.63**	-2.02**	-2.15**	-1.41**	-1.39**
	0.9	-0.22**	-0.26**	-0.92*	-0.98**	-2.08**	-2.14**	-2.59**	-2.91**	-0.78	0.48
	panel	-0.45**	-0.44**	-1.29**	-1.27**	-1.94**	-1.94**	-2.80**	-2.80**	-2.60*	-2.72**
INFL	0.5	0.08	0.07	1.04**	0.94**	2.25**	2.18**	2.52**	2.55**	3.98**	3.95**
	0.7	0.11	0.09	0.86**	0.94**	1.96**	2.16**	2.36**	2.49**	3.25**	3.32**
	0.9	0.04	0.03	0.67**	0.80**	1.52**	1.80**	1.85**	1.69**	2.76**	2.89**
	panel	0.05	0.05	0.92**	0.99**	2.35**	2.47**	3.50**	3.67**	2.91**	3.33**

Note: *,** denote significance at the 10 and 5% level, respectively.

TABLE V

Goodness of fit

	CIR(12)	CIR(24)	CIR(60)	CIR(84)	HL
R^*_G	0.435	0.433	0.440	0.422	0.452
$R^*_{\tau_\kappa}$, τ_k=0.5	0.432	0.458	0.467	0.455	0.538
$R^*_{\tau_\kappa}$, τ_k=0.7	0.411	0.467	0.479	0.474	0.523
$R^*_{\tau_\kappa}$, τ_k=0.9	0.355	0.418	0.438	0.421	0.510
$R^{2-}panel$	0.66	0.64	0.65	0.62	0.64

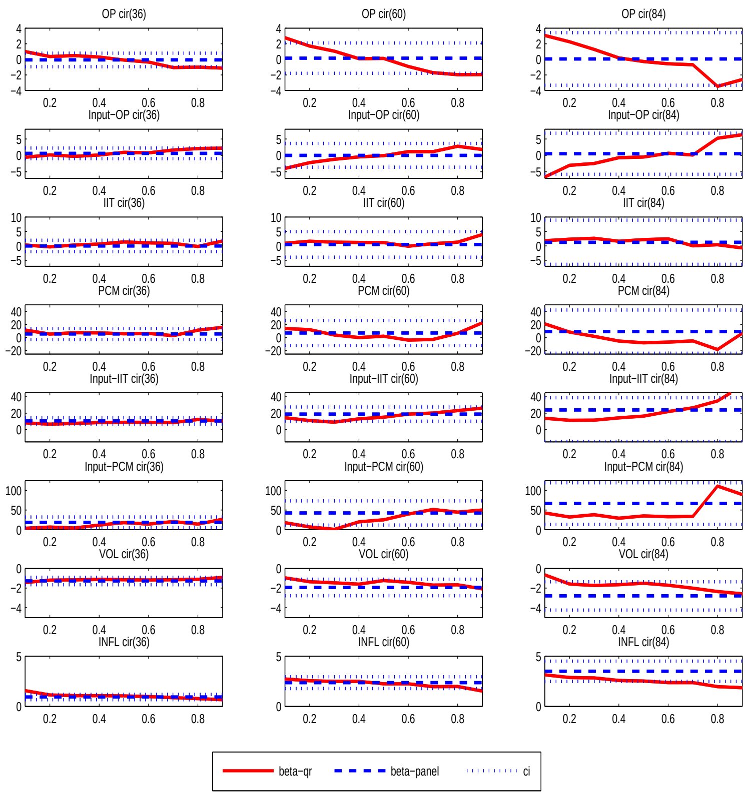

FIG 5. Quantile coefficient estimates.

6. CONCLUSIONS

This paper analyzes sectoral RER persistence for a group of EU-15 countries with the aim of shedding further light on the factors that drive aggregate persistence. We make use of recent theoretical results that establish a link between the aggregate and sectoral impulse response functions which allow us to decompose aggregate persistence into the persistence of its different subcomponents (Mayoral, 2008). We explore the forces that shape aggregate persistence by analyzing the characteristics of the sectors in the upper tail of the distribution of persistence. It is shown that the distribution of sectoral persistence has a large variance and is highly skewed to the right. We show that, as a consequence of the high skewness, the slow reversion to parity of aggregate RERs is driven by a few highly persistent sectors. Interestingly, sectors in the durable category are the most persistent ones and they alone account for more than 40% of the cumulative effect of shocks in the long run. Furthermore, there is a strong link between the overrepresentation of durable goods in the upper quantiles of the distribution of sectoral persistence and the persistence of aggregate RERs as measured by the HL. The correlation between these quantities is greater than 70%, suggesting that understanding why the durable goods category is so persistent is key to explaining aggregate HLs. Further research is needed to explain this phenomenon.

Using trade and industry data, we test whether the traditional theories (non tradability, market structure and price stickiness) are able to account for the pattern of persistence observed in sectoral data. Our results suggest that persistence in the upper quantiles is explained by factors that have to do with the market structure in the intermediate goods market. Since the behavior of the upper quantiles determine, to a large extent the persistence observed at the aggregate level, we conclude that pricing to market and price stickiness are two key factors in explaining the slow reversion to PPP.

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APPENDIX 1

As mentioned in the main text, in addition to Eurostat price data, three additional databases have been used to elaborate the variables employed in Section 5: the United Nation Commodity Trade Statistic Database (Comtrade), the OECD Structural Analysis Statistics (STAN, Edition 2008) and the Input-Output Tables (IOT) from the OECD. These databases use different systems to define the sectors: Eurostat uses the COICOP classification, the Comtrade the HS96 and the OECD the ISIC.

In order to be able to use these databases to elaborate the variables in Section 5, we need first to match the different sectoral classifications. To do so, we have used an alternative classification, the Central Product Classification (CPC, Ver.1.0), for which correspondence tables for the above mentioned classifications exist. More specifically, to obtain the correspondence between the Eurostat (COICOP) and the Comtrade (HS96) classifications, we have matched both the COICOP and the HS96 with the CPC Ver 1.0 classification, with the help of the correspondence tables COICOP-CPC Ver.1.0 and HS96-CPC Ver.1.0), provided by the United Nations Statistics Division. A similar procedure has been followed to match the STAN and the COICOP classifications. In this case, we have employed the correspondence tables COICOP-CPC Ver 1.0 and the ISIC- CPC Ver 1.0, also provided by the United Nations Statistics Division.