Aggregate real exchange rate persistence through the lens of sectoral data

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\textbf{Abstract}

A novel approach to analyzing real exchange rate (RER) persistence and its sources is presented. Using highly disaggregated data for a group of EU-15 countries, it is shown that the distribution of sectoral persistence is highly heterogeneous and skewed to the right, so that a limited number of sectors are responsible for the high levels of persistence observed at the aggregate level. Quantile regression has been employed to investigate whether traditional theories, such as the lack of arbitrage due to nontradability or imperfect competition combined with price stickiness, are able to account for the slow reversion to parity of RERs.

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1. Introduction

Most of the empirical literature on purchasing power parity (PPP) and real exchange rate (RER) persistence focuses on the analysis of aggregate data, where RERs are constructed with aggregate price indices. The general consensus is that aggregate RERs may converge to parity in the long run, although the rate at which this happens is very slow, with half-lives (HL) in the range of 3–5 years (Rogoff, 1996). 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.

Several avenues have been pursued to shed more light on this issue. Recent literature has focused on the analysis of disaggregate real exchange rates, cf. Carvalho and Nechio (forthcoming), Crucini et al. (2010a,b), Crucini and Shintani (2008), Kehoe and Midrigan (2007), Imbs et al. (2005a) and Crucini et al. (2005), etc. One common finding is that there is a considerable degree of heterogeneity across sectors. Nevertheless, the relation between aggregate and sectoral RER persistence is more controversial. Some authors have found large divergences between sectoral and aggregate reversion rates. Using Eurostat data, Imbs et al. (2005a) report standard HL estimates in the range of 3–5 years when aggregate data are used, but considerably smaller, around 1 year, when sectoral data are employed. On the other hand, several authors have found very similar estimates using both types of data, suggesting that the aggregation bias is not a robust feature in the data (Gadea and Mayoral, 2009; Crucini and Shintani, 2008; Chen and Engel, 2005).

The results recently presented in Mayoral (2009) help to clarify the contrasting empirical findings outlined above. She has studied the relations between measures of persistence computed at different aggregation levels and has shown that there is a close connection between them. She proves that the impulse response (IR) function computed with aggregate

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data equals the average of the sectoral impulse responses and that a similar relation also holds for other scalar measures associated with the IR. These results are the starting point of this paper. They imply that since aggregate persistence—as measured by the IR or the associated scalar tools—is completely determined by the behavior of the sectors, the aggregate HL or the cumulative impulse response (CIR) can also be estimated using sectoral data. By using disaggregate information, it is possible to break down aggregate persistence into the persistence of its different subcomponents, thereby obtaining a lot of valuable information about the sources of aggregate persistence. Another interesting implication of her results is that they veil 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 nonrobust measures, a situation where most sectors present relatively 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 investigate the causes of the slow reversion to parity of aggregate real exchange rates through the analysis of sectoral ones. Using highly disaggregate price data on a group of EU-15 real exchange rates (defined against the U.K. pound), a twofold strategy is implemented. First, aggregate RER persistence is broken down into the persistence of its different components. This allows us to identify interesting features of the sources that drive aggregate persistence and to show that it is determined, to a large extent, by the behavior of a limited number of sectors in the upper quantiles of the distribution of persistence. Second, the factors that have traditionally been put forward to account for the slow reversion to parity of RERs, in particular, the lack of arbitrage in nontraded goods and the existence of nominal rigidities combined with pricing-to-market are more thoroughly investigated. Special emphasis is placed on explaining the behavior of the upper (conditional) quantiles of the distribution of sectoral persistence because, as mentioned before, they determine, to a large degree, the persistence observed at the aggregate level. To do so, recent quantile panel regression techniques are employed.

Our main results can be summarized as follows. Firstly, a high degree of heterogeneity as well as high and positive skewness in the speed of reversion of EU sectoral RERs are documented. Sectors belonging to the durable category are those that show the lowest speed of reversion to parity: on average, they account for around 40% of the long-run cumulative effect of shocks to aggregate RERs. By contrast, services present the fastest speed of reversion.

Secondly, our quantile panel regression analysis shows that variables related to the market structure of the intermediate inputs and to the price stickiness of the final goods have a significant effect on sectoral persistence. Furthermore, the impact of these variables tends to be larger, 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 to the tradability of 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 very well. These conclusions are in agreement with modern trade theories (cf. Carvalho and Nechio, forthcoming; Chari et al., 2002).

The rest of the paper is structured as follows. Section 2 presents a brief overview of the literature that has dealt with RER persistence at different levels of aggregation. Section 3 introduces the variables that are used in the paper as well as the different databases employed in their construction. Section 4 provides estimates of aggregate RER persistence computed with both aggregate and sectoral data, tests whether these estimates are equal and explores the distribution of sectoral persistence. Section 5 analyzes whether the traditional theories (lack of arbitrage due to nontradability and/or imperfect competition and price stickiness) are able to explain the distribution of sectoral persistence. Section 6 concludes. An Appendix presents additional explanations not included in the main text.1

2. Related literature

There is a considerable evidence of a large degree of sectoral heterogeneity in the speed of reversion of RERs (Crucini and Shintani, 2008; Imbs et al., 2005a). Starting with the contribution of Imbs et al. (2005a) (IMRR henceforth), several papers have looked at the causal relation between heterogeneity in sectoral exchanges rates and the slow speed of reversion observed at the aggregate level. IMRR show that persistence estimates based on sectoral RERs are, on average, considerably smaller than those obtained for the aggregate rate itself. They argue that estimates of aggregate persistence rely upon the implicit assumption that relative prices converge to parity at the same speed, and that it is precisely the failure to allow for heterogeneity in adjustment dynamics at the sectoral level which induces a positive bias in persistence estimates when aggregate data are employed.

To illustrate their main arguments, consider a very simple model for the sectoral exchange rate in sector i, qi,t, which allows for heterogeneous speed of price adjustment

\[ q_{i,t} = \gamma_i + \alpha_i q_{i,t-1} + v_{i,t}, \]  
\[ v_{i,t} = \rho_i u_{i,t} + e_{i,t}, \]

1 This appendix can be found in the online version of the paper.
where
\[q_{it} = p_{it} - p_{it}^* - s_t.\] (3)
p_{it} and \(p_{it}^*\) are the logs of the price of sector \(i\) in the domestic and foreign countries, respectively, and \(s_t\) is the nominal exchange rate, measured as domestic per foreign currency units. The processes \(u_t\) and \(e_{i,t}\) represent an aggregate and an idiosyncratic shock, respectively, and are assumed to be mutually independent, zero-mean i.i.d. processes. The parameter \(\varepsilon_i\) varies across sectors and captures the heterogeneity in price adjustment dynamics, while \(\rho_i\) measures the impact of the common shock \(u_t\) on sector \(i\). These coefficients are assumed to be draws from the distribution of the random variables \(\varepsilon_i\) and \(\rho_i\). Without loss of generality, the expected value of \(\rho_i\) is normalized to 1. Under the previous assumptions, it is easy to obtain the dynamics of the aggregate RER, \(Q_t\), as the expected value of (1) over the distribution of sectors (Lewbel, 1994).

Recall that the moving average representation of \(q_{it}\) is given by \(q_{it} = \sum_{j=0}^{\infty} \zeta_j^i L^j (\rho^i u_t + e_{i,t}).\) It follows that
\[Q_t = E_i(q_t) = E_i(\rho + \varepsilon_i L + \varepsilon_i^2 L^2 \ldots) u_t + E_i(1 + \varepsilon_i L + \varepsilon_i^2 L^2 \ldots) E_i(e_{1,t}) = \sum_{j=0}^{\infty} E_i(\varepsilon_i^j \rho^i) u_{t-j},\] (4)
where \(E_i(.)\) denotes expectation across the distribution of sectors. For a simple model such as that of (1), IMRR base their sectoral estimates of persistence on the IR of the process \(q_t = \overline{Q}_{t-1} + u_t\), where \(\overline{Q} = E_i(x)\), which is given by
\[IR_{\overline{Q}}(h) = \overline{x}^h.\] (6)

The IR of the aggregate RER to a unitary shock in \(u_t\) can be easily obtained from (4) as follows:
\[IR_{Q}(h) = E_i(x^h \rho).\] (7)

### 2.1. Aggregation bias

IMRR’s main claim is that estimates of the HL obtained from (7) are considerably larger than those obtained from (6). Using Eurostat data, they report estimates of the aggregate HL in the range of 3–5 years, while those based on sectoral data are considerably smaller, around 1 year. They argue that the PPP puzzle is due to a positive bias in aggregate estimates arising because individual heterogeneity is not explicitly taken into account by standard estimates.

Chen and Engel (2005) provide a number of criticisms of the methods of IMRR. From a theoretical point of view, they argue that the analytical results provided by IMRR to justify the aggregation bias are different from the claims made in their empirical work. While in the latter they focus on the behavior of the HL across aggregation levels, analytically they argue that the analytical results provided by IMRR to justify the aggregation bias are different from the claims made in (6).3

These results have been corroborated by Crucini and Shintani (2008). Using a different dataset, an extensive annual micro-panel of individual retail goods and services in local currency prices in major cities from 1990 to 2005, and a different estimation strategy, they find that the aggregation bias is not a robust feature in the data. While they are able to find some evidence for the U.S., they fail to do so for the other locations in their dataset.

Gadea and Mayoral (2009, GM henceforth) have put forward a further objection to IMRR’s methods. They argue that the different persistence behavior of aggregate and sectoral exchange rates reported by IMRR is not due to an upward bias in aggregate data estimates, but rather to a negative bias affecting IMRR’s sectoral persistence measures. Building on the results in Mayoral (2009), GM propose to measure average sectoral persistence by averaging the individual IRs, instead of by averaging the AR coefficients and then computing the IR of the resulting process as in (6). For the simple models considered here, the IR of sector \(i\) to a unitary change in the aggregate shock \(u_t\) is given by \(IR_{Q_i}^u(h) = x^h_i \rho_i.\)4 Averaging across sectors, it is obtained that
\[\overline{IR}_{Q_i}^u(h) = E_i(x^h_i \rho_i).\] (8)

Defining the aggregation bias (AB) as the difference between the aggregate and the average of the sectoral IRs to a unitary shock in \(u_t\), it is easy to see that
\[AB = IR_{Q}(h) - \overline{IR}_{Q_i}^u(h) = 0 \quad \text{for all } h.\] (9)

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3 It is also assumed that the support of \(x\) is strictly smaller than 1, that \(\sum_{j=0}^{\infty} E(\varepsilon_i^j) < \infty\) and that \(e_{i,t}\) is independent from \(x\). The assumptions in this section are only imposed to simplify the explanation and the main arguments are valid in a more general setting (see Mayoral, 2009 for details).

4 However, Imbs et al. (2005b) replied to this paper and showed that their results survive each of the criticisms raised by Chen and Engel.

4 See Mayoral (2009) for details.
It follows that since the IR is a highly nonlinear function, averaging the AR coefficients and then computing the IR, as IMRR do, or averaging the individual responses, may yield very different results. In fact, Jensen’s inequality ensures that, for most empirically relevant cases, the former measure is smaller than the latter. The intuition of this result is clear: since the IR function is convex, highly persistent sectors increase the mean considerably. However, in the computations of IMRR, these sectors are eliminated in the first stage when the model AR coefficients are averaged. This translates, not surprisingly, into lower estimates of persistence. Using similar data and a similar estimation strategy to those employed in IMRR’s paper, GM have shown that the aggregation bias is not statistically different from zero.

### 2.2. Total heterogeneity effect

More recently, Carvalho and Nechio (forthcoming, henceforth CN) have introduced a theoretical model with sticky prices that departs from the existing literature by allowing for heterogeneity in the frequency of price changes across sectors. To gauge the impact of allowing for heterogeneity, they compare the persistence implied by two models sharing the same average frequency of price changes, one that allows for heterogeneity and another that does not. They denote as total heterogeneity effect (THE) the difference in persistence implied by these two models. This quantity is further broken down into two components: a counterfactuality effect (CE) and an aggregation effect (AE). Using the IR(h) as the persistence measure, these effects can be defined as \( \text{THE} = \text{IR}_h - \text{IR}_r(h) = \text{CE} + \text{AE} \), where

\[
\begin{align*}
\text{CE} &= \text{IR}_h - \text{IR}_r(h), \\
\text{AE} &= \text{IR}_h - \text{IR}_r(h),
\end{align*}
\]

and \( \text{IR}_h(h) \) is the sectoral average of the response of \( q_{it} \) to a unitary change in the reduced-form shock \( v_{1t} \), given by

\[
\text{IR}_h(h) = E(\varsigma^h).
\]

CN use this decomposition to account for the different results found in the literature. They argue that while both AE and CE are strictly greater than zero, the latter accounts for the largest part of THE. Thus, since different authors have reported estimates of different quantities (IMRR provide estimates of THE and GM and Crucini and Shintani, 2008 of AE), different results are bound to arise.

Notice that AB and the AE, defined in (9) and in (11), respectively, are very similar. The difference between them stems from the shocks that are assumed to change when computing the IRs. CN consider a unitary change in the aggregate shock, \( u_t \), and a unitary change in the reduced-form shock, \( v_{1t} \), to compute the aggregate and the individual IRs, respectively. On the other hand, in the computation of AB, the aggregate and the individual IRs are both based on unitary changes in the aggregate shock \( u_t \).

Notice further that, under independence of \( \varsigma \) and \( \rho \), \( \text{IR}_h(h) = E(\varsigma^h \rho) = E(\varsigma^h) = \text{IR}_r(h) \), which implies that \( \text{AE} = \text{AB} = 0 \), that is, there is no aggregation effect even if the individual IRs are computed with respect to their reduced-form shock \( v_{1t} \). If \( \varsigma \) and \( \rho \) are not independent, the direction of the correlation between \( \varsigma^h \) and \( \rho \) will determine whether AE is positive or negative. In CN’s model, this correlation is actually positive (meaning that higher \( \varsigma \)’s obtain greater weights, on average) and this is why they obtain that \( \text{AE} > 0 \). If the correlation were negative, however, the opposite would be obtained. CN’s observation that AE is small in Eurostat data can be interpreted as saying that the correlation between \( \varsigma^h \) and \( \rho \) is close to zero.

In the following sections, the relation established in (9) will be exploited to investigate the sources of aggregate persistence by analyzing sectoral RERs. Considering aggregate and sectoral IRs related to the same macro-shock has two advantages: firstly, it enables a better understanding of the role of aggregation in the transmission of shocks, since the same shock is hitting both the sectors and the aggregate process; and, secondly, it allows us to pin down a close relation between sectoral and aggregate behavior. Since \( \text{IR}_q \) and \( \text{IR}_r \) are the same function, aggregate persistence can be estimated using either sectoral or aggregate data. The use of sectoral data yields considerably more efficient estimates as will be shown in Section 4 and, more importantly, it allows us to break down aggregate persistence into the persistence of its subcomponents.

### 3. The data

This section provides definitions of the variables employed in this paper and describes the sources employed in their elaboration.

To construct sectoral RERs, the Eurostat Harmonized Index of Consumer Prices (HICP) for 11 European countries ranging from 1996:1 to 2007:12 have been employed. These countries and their corresponding abbreviations are Austria (AU), Belgium (BE), Denmark (DK), Finland (FI), France (FR), Germany (GE), Italy (IT), the Netherlands (NL), Spain (SP), Sweden (SW) and the United Kingdom (UK).\(^5\) Eurostat provides data corresponding to different levels of aggregation. We

\(^5\) All the EU-15 countries were initially considered. However, four of them (Portugal, Luxembourg, Greece and Ireland) present important data shortages in the other datasets employed in this paper. For this reason, they were dropped from the analysis.
focus on the most disaggregate level, which contains prices from 94 sectors. Nominal exchange rates are obtained from the Main Economic Indicators of the OECD and sectoral RERs are defined against the U.K. pound according to (3). Aggregate RERs have been constructed by aggregating sectoral RERs using Eurostat price weights.\(^6\)

Section 5 uses a number of variables to account for the persistence of European sectoral exchange rates. These variables belong to three categories: those that are a proxy for market structure and price stickiness, those that measure the degree of openness of the sectors, and some controls. Four datasets have been employed to construct them: the Comtrade (United Nations Commodity Trade Statistic Database), the OECD Structural Analysis Statistics (STAN, Edition 2008), the Input–Output Tables (IOT) from the OECD and data on the frequency of price changes (see Dhyne et al., 2006 and the references therein).\(^7\) While definitions of these variables are provided below, their connections with RER persistence are spelled out in Section 5.

### 3.1. Market structure and price stickiness

Two proxies for market structure have been elaborated, the price-cost margin and the intra-industry trade index.

#### 3.1.1. Price-cost margin (PCM)

The PCM index proxies the degree of profitability of an industry. It is defined as

\[
\text{PCM}_{c,i} = \frac{V_{A_{c,i}} - W_{c,i}}{V_{A_{c,i}} + CM_{c,i}},
\]

where \(V_{A_{c,i}}\) is the total value added of sector \(i\) (the value of total production minus the cost of materials) in country \(c\), \(W_{c,i}\) is the labor compensation and \(CM_{c,i}\) denotes the cost of materials. In addition, the PCM of the inputs employed in the production of good \(i\) has been computed as follows:

\[
\text{Input-PCM}_{c,i} = \sum_{g=1}^{C} \omega_{g} \text{PCM}_{c,g},
\]

where \(\text{PCM}_{c,g}\) is the price-cost margin of input \(p\) defined as in (13) and \(\omega_{g}\) and \(G\) denote the share of good \(g\) and the total number of inputs involved in the production of sector \(i\), respectively. The weights \(\omega_{g}\) are the relative contribution of the corresponding input \(g\) to the production of good \(i\), as stated by the Input–Output Tables of country \(c\).

#### 3.1.2. Intra-industry trade (IIT)

The IIT refers to the exchange of products belonging to the same industry and characterizes the nature of competition via the substitutability between domestic and foreign products. Two different indices have been computed, one that evaluates the degree of IIT for sector \(i\) in country \(c\) and another that measures the amount of IIT associated with the intermediate items needed to produce good \(i\). The IIT index for sector \(i\) in country \(c\) is defined as in Grubel and Lloyd (1975)

\[
\text{IIT}_{c,i} = 1 - \frac{\sum_{j=1}^{R_{i}} |X_{c,j} - M_{c,j}|}{\sum_{j=1}^{R_{i}} (X_{c,j} + M_{c,j})},
\]

where \(R_{i}\) is the number of goods (at six digits of disaggregation) in sector \(i\) according to the Comtrade database and \(X_{c,j}\) (\(M_{c,j}\)) represents total exports (imports) of good \(j\) in country \(c\).

The intermediate-goods IIT index (denoted as Input-IIT) is computed as the weighted average of IIT indices for each of the inputs employed in the elaboration of good \(i\), that is

\[
\text{Input-IIT}_{c,i} = \sum_{g=1}^{G} \omega_{g} \text{IIT}_{c,g}.
\]

#### 3.1.3. Price stickiness

To proxy for price stickiness, data on the frequency of price changes at the sectoral level are usually employed. Unfortunately, for most of the countries in our dataset, data with ample and homogenous product coverage does not seem to be available.\(^8\) In spite of this limitation, a rough proxy of price stickiness has been elaborated as follows. Firstly, Kehoe and Midrigan (KM, 2007)’s data have been employed. They provide estimates of the per period probability of no-price adjustment corresponding to 57 sectors for AU, 56 for FR, 46 for BE and 31 for SP. Secondly, for the countries not considered in KM, the data summarized by Dhyne et al. (2006) have been considered. They select a representative 50-product sample with good coverage for 10 European countries. These products have been assigned to the different

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\(^6\) The weights employed to aggregate sectoral RERs are the average over the period 1996–2007 of those used to aggregate sectoral prices in the different countries. Price data on some sectors are missing for some countries. See Eurostat for more details.

\(^7\) See the Appendix for more details on these datasets.

\(^8\) For some countries, such as AU and BE, the number of product categories for which frequencies of price changes are recorded is high (639 and 583, which amounts to 90 and 68% of total CPI, respectively) but for the others, it is only around 50 products (10% of total CPI).
Eurostat sectors following a similar criteria to KM. This allows us to obtain frequencies of no-price adjustment corresponding to approximately 30 sectors for the countries not included in KM study, with the exception of SW and DK. Since the amount of missing data is very large, two versions of the infrequency of price adjustment have been elaborated. The first one (STICK) fills in the missing values as follows: if data on the probability of no-price adjustment of sector $j$ in country $c$ is missing but there is information for other countries, the average of the available infrequencies for sector $j$ is assigned. The second version (STICK2) does not fill in missing values.

The procedure above is far from ideal since information on many sectors is missing and, with the exception of AU, BE and FR, the quality of the estimates of the remaining sectors is questionable. To overcome these limitations, a different measure of openness of the intermediate inputs has also been calculated. It is defined as the proportion of the Input-OP of the intermediate inputs to the GDP of the corresponding good (although not by its average level of inflation). This suggests that the volatility of inflation could potentially be used as a proxy for price stickiness. We have regressed KM’s sectoral inflation on the mean and the standard deviation of sectoral inflation. A similar regression has been performed using the data elaborated with Dhyne et al. (2006)’s sample. In both cases, the coefficient associated with the volatility of sectoral inflation has also been used to proxy for price stickiness. According to this interpretation, sectors with larger inflation volatility would tend to present less persistent RERs. The volatility of inflation, \( \text{VOL}_{c,i} \), is defined as the standard deviation of the inflation rate of sector $i$ in country $c$, which is defined as \( \text{INFL}_{c,i} = 1200(p_{c,i,t} - p_{c,i,t-1}) \).

### 3.2. Tradability of goods

Tradability of sector $i$ is proxied by its degree of openness, defined as

\[
\text{OP}_{c,i} = \frac{X_{c,i} + M_{c,i}}{\text{GDP}_{c,i}},
\]

where \( \text{GDP}_{c,i} \) is the total GDP of sector $i$ in country $c$ for 2003. As for the group of variables related to market structure, the degree of openness of the intermediate inputs has also been calculated. It is defined as Input-OP, where \( \text{OP}_{g} \) denotes the degree of openness of the intermediate good $g$, computed as in (17).

### 3.3. Control variables

The level of inflation in sector $i$ has been employed as an additional control. To this effect, the variable \( \text{INFL}_{c,i} \), defined as the average of \( \text{INFL}_{c,i} \) over the period 1996–2007, has been considered.

### 4. Aggregate persistence and aggregation bias

This section describes the econometric models and methods employed to estimate IRs and other persistence measures. In addition, it formally tests the existence of an ‘aggregation bias’ in European RERs. Finally, it provides a description of the distribution of sectoral persistence.

#### 4.1. Econometric models and methods

It is assumed that sectoral RERs follow a linear specification, similar to that in (1) and (2). More specifically, the RER of sector $i$ in country $c$ at time $t$, \( q_{c,i,t} \), is given by

\[
q_{c,i,t} = \alpha_{c,i} + \sum_{k=1}^{K} \beta_{k} q_{c,k,t} + \epsilon_{c,i,t}, \quad \epsilon_{c,i,t} = \rho_{c,i} u_{c,i} + \epsilon_{c,i} \quad \text{for } t = 1, \ldots, T, \ i = 1, \ldots, N. \tag{18}
\]

As shown by Lewbel, the aggregate of (18) follows an AR (\( \infty \)) process. Thus

\[
Q_{c,i} = \sum_{j=0}^{\infty} A_{j} Q_{c,i-j} + u_{c,i} \tag{19}
\]
4.2. Estimation

Sectoral IRs, defined as the responses of $q_{it}$ to unitary changes in $u_t$ and $v_t$, have been considered. The impulse response of sector $i$ to a unitary change in $u_t$ or $v_t$ is given, respectively, by $IR_{tq}^u(0) = \rho_i$ and $IR_{tv}^v(0) = 1$ and

$$IR_{tq}^u(h) = \sum_{k=1}^{h} a_{ik} IR_{tq}^u(h-k) \quad \text{for } g = \{u,v\} \text{ and } h \geq 1. \quad (20)$$

Average sectoral persistence is computed as the mean of the individual IRs, that is, $\overline{IR}_{tq}^u(h) = \sum_{i=1}^{N} \omega_i IR_{tq}^u(h)$, for $g = \{u,v\}$, where $\omega_i$ are Eurostat sectoral weights.

The IR of $Q_i$ to a unitary change in $u_t$ is given by $IR_{tq}(0) = 1$ and

$$IR_{tq}(h) = \sum_{j=1}^{h} A_{ij} IR_{tq}(j-1) \quad \text{for } h \geq 1. \quad (21)$$

Since $IR(h)$ is a vector of numbers, it is customary to use scalar measures. Two of these scalar tools are employed: the half life (HL) and the cumulative impulse response (CIR). The HL is defined as the value of the IR(h) that satisfies $IR_{tq}(t,h=HL) = 0.5$, or, alternatively, $\overline{IR}_{tq}(h=HL) = 0.5$ if sectoral data are employed.13 The cumulative impulse response (CIR) at horizon $h$ is defined as $\text{CIR}(h) = \sum_{l=0}^{h} IR_{tq}(t,l)$, or, equivalently, $\text{CIR}(h) = \sum_{l=0}^{h} \overline{IR}_{tq}(l)$.

4.3. Testing

To obtain estimates of the IRs and the scalar measures of persistence, the following methods have been employed.14 In the presence of sector heterogeneity, $Q_t$ might display complicated dynamics, as Eq. (19) shows. Following Kuersteiner (2005), AR($K$) models have been fitted to aggregate RERs, where $K$ has been chosen according to the general-to-specific (GTS) approach (Ng and Perron, 1995).15 Since RERs are, in general, highly persistent, bias-corrected estimates have been computed (see the Appendix). Then, estimates of $IR_{tq}$ have been obtained based on expression (21).

To estimate $\overline{IR}_{tq}(h)$, bias-corrected AR($k$) processes have been fitted to all sectors, the resulting estimates have been plugged to (20) and a weighted average of the individual IRs has been calculated. Estimation of $\overline{IR}_{tq}(h)$ is similar, the only difference being that, in this case, estimates of all the model parameters, $a_{ik}$ and $\rho_i$, are required. See the Appendix for a description of how estimates of $\rho_i$ are obtained.

Confidence intervals for the IRs have been calculated using bootstrap methods. Details are provided in the Appendix.

4.4. Empirical results

Fig. 1 presents the plots of our estimates for $IR_{tq}$ and $\overline{IR}_{tq}$ as well as their confidence bands at the 5% significance level for each of the countries in our dataset. Estimates of $\overline{IR}_{tq}(h)$ are not reported to enhance visibility, since they are basically identical to those of $IR_{tq}(h)$. These plots show that, although European Union markets are very integrated, EU RERs are highly persistent. Estimates of the IRs based on aggregate and sectoral data are, in general, very similar, as predicted by the

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13 As in Kilian and Zha (2002), the HL is defined as the largest value of HL such that $IR_{tq}(t,HL-1) \geq 0.5$ and $IR_{tq}(t,HL+1) < 0.5$.
14 As a preliminary analysis, panel unit root tests have been applied to EU RERs (Levin et al., 2002; Im et al., 2003). The results, not reported for reasons of space, show that the unit root hypothesis could be rejected in most cases, in line with the previous literature. In accordance with these results, the estimation of the parameters has been restricted, so that the sum of the autoregressive coefficients is smaller than 1.
15 Kuersteiner (2005) has shown that, if the GTS approach is employed to select $K$, consistent and asymptotically normal estimates of the coefficients of an AR ($\infty$) process can be obtained. In the present paper, a maximum of 36 AR terms has been employed throughout.
theoretical results in Section 2. Interestingly, estimates based on sectoral data are considerably more efficient than those based on aggregate persistence, as shown by the fact that the confidence bands associated with $IRQ$ are considerably wider than the sectoral ones.

Table 1 displays some summary statistics corresponding to the estimated IRs, namely, the HL and three values of the CIRc $ðh$ for $h$ corresponding to 1, 3 and 5 years). $Q$, $q^u$ and $qv$ denote CIR or HL measures obtained from $IRQ$, $IRu$ and $IRv$, respectively. The values of the HLs are in line with those found in previous studies displaying values between 3 and 5 years. In addition, the different measures of aggregate persistence computed with aggregate and disaggregate data are very close, corroborating the graphs in Fig. 1.

In view of Table 1, it is not surprising that the null hypotheses $H_0^A$, $H_0^B$ and $H_0^C$ cannot be rejected for any of the countries in our dataset (the corresponding figures are reported in the Appendix). This has two important practical implications: firstly, the fact that $H_0^A$ cannot be rejected implies that considering sectoral IRs that refer to changes in the aggregate or the sectoral RERs for the group of European countries considered in this study.

![Fig. 1. Aggregate IRs estimated with aggregate and sectoral data. Note: This graph shows the IR to an aggregate shock estimated using both aggregate (IR-Q) and sectoral (IR-q^u) RERs for the group of European countries considered in this study.](image-url)

Table 1

<table>
<thead>
<tr>
<th></th>
<th>Cumulative impulse response (h)</th>
<th>HL</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>12</td>
<td>36</td>
</tr>
<tr>
<td>Q</td>
<td>q^u</td>
<td>q^v</td>
</tr>
<tr>
<td>AU</td>
<td>9.55 8.60 8.55</td>
<td>22.59 18.99 19.08</td>
</tr>
<tr>
<td>BE</td>
<td>9.05 8.59 8.59</td>
<td>23.04 20.22 20.21</td>
</tr>
<tr>
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<td>27.42 21.24 20.76</td>
</tr>
<tr>
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</tr>
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<td>23.96 22.04 22.03</td>
</tr>
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<td>10.35 8.61 8.59</td>
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<tr>
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</tr>
<tr>
<td>SW</td>
<td>8.87 8.15 8.38</td>
<td>17.88 17.48 18.33</td>
</tr>
</tbody>
</table>

Note: $Q$, $q^u$ and $q^v$ denote CIR or HL measures obtained from $IRQ$, $IRu$ and $IRv$, respectively.
reduced-form shock is irrelevant in our sample. Since $IR^v(h)$ is easier to compute, the rest of the paper will use this function to derive the scalar measures of sectoral persistence. To simplify the notation, the superindex ‘$v$’ will be dropped hereinafter. Secondly, the fact that neither $H^0_B$ nor $H^0_C$ could be rejected implies that estimates of aggregate persistence can also be obtained by averaging sectoral estimates.

4.5. The distribution of sectoral persistence

Many studies have documented the existence of a high degree of heterogeneity in the persistence of sectoral RERs (see Imbs et al., 2005a; Crucini and Shintani, 2008, for recent references) and the dataset considered in this paper is not an exception. Density functions corresponding to CIR($h$) for different values of $h$, namely, $h$=$\{36, 60, 84\}$ months, have been estimated for all the countries in our dataset. In addition to a considerable degree of heterogeneity, the densities display substantial skewness to the right, which is higher, the longer the horizon of the CIR considered. Average skewness is 0.7810, 1.1779 and 1.8150 for $h$=$\{36, 60, 84\}$, respectively. Since persistence is a long-term property, the pattern of the densities of the different CIR indicates that persistence is highly heterogeneous and asymmetric and that these characteristics are accentuated with the horizon considered. These two features have an immediate implication on the aggregate IR; since it is an average of the individual responses and averages are very nonrobust measures, it will be most likely driven by a few highly persistent sectors.

4.5.1. Persistence by groups of sectors

To look more closely at the distribution of sectoral persistence, the sectors, ranked by their persistence level, have been grouped into five categories. To make the different groups as homogeneous as possible, the size of the bins has been determined such that the variance around the bin’s average persistence is kept fixed. This gives us a number of sectors per bin of 2, 21, 34, 19 and 2 for bins 1–5, respectively. See the Appendix for a list of the sectors included in each bin. The left-hand graph in Fig. 2 plots the IRs associated with each of these bins. As this figure shows, the persistence implied by the sectors in bins 1–3 is very different. The IRs of bins 1–3 present a relatively quick reversion to parity as opposed to those of bins 4 and, more especially, 5, which do not display clear signs of mean reversion.

To compare this classification with traditional ones, two long-established categories have also been considered. The first classifies goods as food (F), durables (D), nondurables (ND), services (S) and energy (E). The second one, as traded (T) and nontraded (NT). The right-hand graph in Fig. 2 depicts the IRs corresponding to the first of these categories. It shows that they are considerably closer together than those in the left-hand side of this figure, suggesting the existence of

---

16 See the Appendix for details on the estimation and graphs of the densities.
17 Estimates have been obtained using the panel described above. Sectors have been ranked according to their IR evaluated at $h=HL$ since this measure allowed us to construct bins with very similar within-group variability. Alternative measures of persistence have been employed and the results were qualitatively identical. A genetic algorithm was employed to assign sectors to bins.
18 Services are considering as NT (with the exception of air travel and financial services) while all other sectors are considered as traded.
important within-group heterogeneity. D and ND are as the most persistent groups of sectors while the IRs corresponding to F, E and S decay more quickly. Exploring the internal composition of the persistence bins lead to similar conclusions: although bin structure changes as the degree of persistence increases, there is considerable heterogeneity within each bin. Services tend to be concentrated in the least persistent bins. The 26 sectors in the service category are mainly located in the first three bins (2, 13 and 10 sectors in bins 1–3, respectively) and only one (financial services) is located in bin 5. By contrast, durables are usually found in the most persistent ones. The number of durable sectors in bins 1–5 is 0, 1, 11, 10 and 1, respectively. On the other hand, sectors in the ND, E and F categories tend to be spread over the intermediate bins (2–4). While F and E are quite homogeneously spread over bins 2–4, ND are slightly more concentrated towards bins 3 and 4. In view of the previous results, it is not surprising to see that nontradables are, in general, less persistent than tradables. Of the 29 sectors in the NT category, only 1 is located in bin 4 and none in bin 5. The opposite behavior is found for traded goods, which clearly dominate in the most persistent bins.\footnote{Graphs on the composition of the bins are reported in the Appendix.}

The heterogeneous composition of the bins shows that there is no clear-cut relationship between traditional categories and persistence. This result underscores the fact that these classifications may not be the optimal way to organize our analysis of RER persistence. The traded versus nontraded distinction seems to be particularly problematic for this purpose. Although it is clear that this result may derive, in part, from the fact that CPI-based RERs for traded goods contain a substantial amount of nontraded inputs, which blurs the differences between traded and nontraded goods in our data, it also suggests that other forces than the lack of arbitrage may be driving the persistence of RERs.

### 4.5.2. Sectoral contribution to persistence

To explore the above-mentioned trends further, the contribution of each sector and group of sectors to aggregate persistence has been quantified. Using Eq. (9), it is possible to evaluate the percentage contribution of group \( j \) to the aggregate IR at horizon \( h \), denoted as \( PC_{C,j}(h) \), as

\[
PC_{C,j}(h) = \frac{\sum_{i=1}^{N_j} \omega_j \cdot IR_{Q}(t,h)}{IR_Q(t,h)} ,
\]

where \( \omega_j \) is the weight associated with sector \( i \) in group \( j \), and \( N_j \) is the number of sectors in group \( j \), with \( \sum_{j=1}^{J} N_j = N \). Thus, the percentage contribution of group \( j \) to the aggregate cumulative response, \( PC-CIR_{C,j}(h) \), is defined as \( PC-CIR_{C,j}(h) = \sum_{i=1}^{N} PC_{C,i}(h) \). Similarly, the relative contribution of group \( j \) to the aggregate HL of country \( c \), denoted as \( PC-HL_{C,j} \), has been computed as \( PC-HL_{C,j} = \sum_{i=1}^{N_j} \omega_j \cdot IR_Q(t,h=HL)/IR_Q(t,h=HL) \).

Table 2 presents the estimated values of the PC-HL and the PC-CIR(h) corresponding to the two traditional classifications considered above. 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 labeled as food is 23%. This column is included so that it is possible to evaluate whether the percentage contribution to total persistence is larger or smaller than the percentage weight in the aggregate RER. Columns 2–4 displays the average percentage contribution of the group of sectors to the aggregate CIR(h), \( PC-CIR_{C,j}(h) \), for three different values of \( h = \{12, 36, 60\} \). The last column presents the contribution to the HL, \( PC-HL_{C,j} \), for each of the groups.

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 longer horizons are analyzed, the picture changes substantially. Durable goods become the group with the highest contribution to long-run persistence. This result underscores the fact that these classifications may not be the optimal way to organize our analysis of RER persistence. The traded versus nontraded distinction seems to be particularly problematic for this purpose. Although it is clear that this result may derive, in part, from the fact that CPI-based RERs for traded goods contain a substantial amount of nontraded inputs, which blurs the differences between traded and nontraded goods in our data, it also suggests that other forces than the lack of arbitrage may be driving the persistence of RERs.

Their long-run contribution to the CIR exceeds their initial weights by 60% and 50%, 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) is only 60% that of their initial weight for energy, and 76% in the case of services. The traded/nontraded goods categories also display 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 CIR(60) (38%) exceeds its corresponding initial weight (27%) by 41%. 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 60% and 50%, 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) is only 60% that of their initial weight for energy, and 76% in the case of services. The traded/nontraded goods categories also display 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 CIR(60) (38%) exceeds its corresponding initial weight (27%) by 41%. 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 60% and 50%, 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) is only 60% that of their initial weight for energy, and 76% in the case of services. The traded/nontraded goods categories also display 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 CIR(60) (38%) exceeds its corresponding initial weight (27%) by 41%. 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 60% and 50%, 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) is only 60% that of their initial weight for energy, and 76% in the case of services. The traded/nontraded goods categories also display 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 CIR(60) (38%) exceeds its corresponding initial weight (27%) by 41%. 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 60% and 50%, 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) is only 60% that of their initial weight for energy, and 76% in the case of services. The traded/nontraded goods categories also display 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 CIR(60) (38%) exceeds its corresponding initial weight (27%) by 41%.

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5. Accounting for RER persistence

The goal of this section is to investigate whether there is a plausible theoretical explanation for the cross-sectional persistence patterns identified in the previous section. 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. Standard regression methods only provide a single summary measure of the conditional distribution of the dependent variable (the conditional mean), given the predictors. However, the corresponding estimates are not necessarily indicative of the response of the dependent variable to the regressors in 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.

Explanations of the slow convergence to PPP have traditionally been 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, arbitrated (Swan, 1960; Salter, 1959); 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) (Crucini et al., 2010b; Carvalho and Nechio, forthcoming; Chari et al., 2002); 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 (Engel, 1993). By focusing on harmonized sectoral price data, it is reasonable to discard different consumption preferences as a source of deviations from PPP since disaggregate prices for a homogeneous basket of goods are considered. Thus, in this section, only the first two potential explanations are explored.

In what follows, the set of independent and dependent variables used to test the theories above, the econometric techniques employed in our empirical exercise and the results obtained are discussed.

5.1. Independent and dependent variables

This section presents the theoretical connections between the variables introduced in Section 3 and the persistence of RERs.

5.1.1. Market structure and price stickiness

Intra-industry trade (IIT): Faruqee (1995) has shown that sectors with a larger degree of intra-industry trade exhibit a greater degree of PTM which, in turn, leads to more persistent RERs. The intuition is clear: in the presence of intra-industry
trade, domestic and foreign firms supply product varieties that are differentiated but still mutually substitutable. Thus, exporting firms will have some pricing power for their differentiated products and, due to the existence of substitutability between domestic and foreign product varieties, will tend to stabilize their prices in local currency terms, which will increase price rigidities. Since domestic and foreign products are more substitutable in intra-industry trade, \textit{ceteris paribus}, a greater degree of intra-industry trade leads to more persistent exchange rates.

The existence of PTM at the intermediate goods level can also have an impact on the persistence of the relative price of the final goods. As firms use other firms’ output as inputs, their prices tend to move more closely together. Thus, the stickiness of the intermediate goods can endogenously increase the stickiness of final goods prices and spill over from one firm to another (Kehoe and Midrigan, 2007). The index \textit{Input-\textit{IIT}_c,i} tries to capture this effect. A positive relation between this variable and RER persistence is expected.

\textit{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. The higher the value of the PCM, the lower the competition in that sector. Thus, a large value of this variable will be associated with a high pricing power that could lead to PTM and to more persistent RERs (Faruqee, 1995). The degree of competition at the intermediate goods level is measured by \textit{Input-PCM}_c,i and, for similar reasons as above, a larger value of this variable will be associated with stickier final goods prices and, thus, with more persistent RERs.

\textit{Price stickiness}: A classic explanation for the persistence of RERs is that they are the result of money shocks interacting with sticky prices (Dornbusch, 1976). Kehoe and Midrigan (2007) and Carvalho and Nechio (forthcoming) present models where the persistence of sectoral real exchange rates depends explicitly on the frequency of price adjustments in the sector. In these models, the lower the frequency of price adjustment, the higher the persistence of RERs.

5.1.2. Tradability of goods

\textit{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. Bergin and Feenstra (2001) and Faruquee (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.\textsuperscript{21} As before, the degree of openness of the intermediate inputs has also been calculated (\textit{Input-\textit{OP}_c,i}). For similar reasons, a negative relation between this index and the persistence of deviations from PPP is expected.

5.1.3. Control variables

\textit{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). Thus, a negative relation between inflation and persistence is expected.

Following previous studies, other control variables, such as government spending and the volatility of the exchange rate (see Cheung et al., 2001) were also considered. 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, they were not included in the benchmark specifications.

5.1.4. Dependent variables

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

5.2. Econometric methods

In order to examine the empirical relations between RER persistence and the various theories outlined above, both a standard and a quantile panel regression analysis have been carried out. The following model for the conditional quantile \textit{t} associated with the response of the corresponding persistence measure in sector \textit{i} of country \textit{c} has been considered (Koenker, 2004):

\[ Q_{\beta c i}(\tau|\mathbf{x}_{ci}) = \alpha_i + \mathbf{x}_{ci}^T \beta(\tau), \quad i = 1, \ldots, N, \quad c = 1, \ldots, C, \]

where \((\mathbf{y}_{ci}, \mathbf{x}_{ci})\) denote the values of the dependent and independent variables, respectively. See the Appendix for further details on the estimation strategy.\textsuperscript{22} With respect to the standard panel regression analysis, the following model has been

\textsuperscript{21} Other approaches to measure the degree of openness of the final and the intermediate goods, such as transportation costs, proxied by the distance between national capitals, have also been tried. Alternatively, trade barriers have also been measured as in Anderson and van Wincoop (2003) and Novy (2008). None of these variables turned out to be significant or had any significant impact on the coefficients of the other variables, so they were dropped from the analysis.

\textsuperscript{22} Estimates have been obtained by using an R code provided by the author.
considered:
\[ y_{t,i} = \theta_i + \chi_{t,i}^\prime \beta + u_{t,i}, \]  

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

Four models have been estimated: M1 (A and B) includes all the regressors mentioned in Section 5.1 while M2 (A and B) only contains the variables that turned out to be significant in the regressions performed in M1. Models 1A and 2A use VOL as a proxy for price stickiness while Models 1B and 2B use STICK. Conditional quantile regressions for all the deciles have been computed although, for the sake of brevity, full regression results are only presented for the quantiles \( \tau \in \{0.5, 0.7, 0.9\} \).

Table 3 presents the estimated coefficients and, to save space, only figures corresponding to models M2A and M2B are reported. The conclusions obtained in the larger models were identical and can be summarized as follows. The most important group of variables to account for RER persistence appear to be those related to 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. It is remarkable that the coefficients associated with these variables tend to increase considerably the farther the horizon of the CIR and the higher the quantile considered.

Interestingly, after controlling for the market structure of the intermediate inputs, the market structure of the final goods turns out not to be important in explaining RER persistence. Both IIT and PCM have the expected positive signs but they are not significant. This result underscores the importance of price complementarities in explaining RER persistence. PTM at the intermediate goods level makes prices across firms move in a similar way, so that price stickiness spills over

### Table 3

<table>
<thead>
<tr>
<th>( \tau )</th>
<th>Cumulative impulse response (( h ))</th>
<th>HL</th>
</tr>
</thead>
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<tr>
<td>0.5</td>
<td>1.40a</td>
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<td>0.7</td>
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<td>0.9</td>
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</tr>
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<tr>
<td>Panel</td>
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<td>-0.04</td>
</tr>
</tbody>
</table>

Note: This table presents the results of the quantile and standard panel estimation. M2A and M2B uses VOL and STICK as proxies for price stickiness.  

* Denote significance at the 5% level.  

b Denote significance at the 10% level.

The variable STICK2 was also employed (see its definition in Section 3). The results were, in general, weaker. This is not surprising since, for most countries, only around 30 sectors were employed in the regressions.

The correlation between the two sets of measures is high: 0.30 for IIT and input-IIT and 0.45 for PCM and its corresponding input. If the input variables are not included in the regression, those of the final goods are generally significant.
from one firm to another (Kehoe and Midrigan, 2007). Our results suggest that the impact of this spillover is key in determining persistence at the aggregate level and, once it has been accounted for, the market structure of the final goods is no longer relevant.

The degree of price stickiness, as measured by STICK, does not have a significant impact on RER persistence. However, this result should be taken with caution given the limitations of this variable described above. Nevertheless, and in line with the theoretical predictions, a higher degree of inflation volatility is associated with a lower degree of persistence, as captured by the negative sign of the variable VOL, which is highly significant in all models. Interestingly, the coefficients of the quantile regression parameters are considerably larger in absolute value as farther horizons and higher quantiles are considered. Finally, the estimated coefficients for the remaining variables are fairly similar independently of the proxy of price stickiness employed.

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 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. 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; Chari et al., 2002) and, therefore, this distinction is not key in accounting for persistence. Another aspect that may 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 involves nontraded components as well, such as marketing and distribution services. In addition, the European Union 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/nontraded categories are less important than in other geographical areas.

The effect of inflation is puzzling. This variable has a positive and very significant effect on RER persistence, indicating that a higher level of inflation is related to higher persistence levels, the opposite of what the theory predicts. Further research is needed to identify the forces that drive this positive relationship.

The results of the standard panel regression are very much in line with the discussion above. However, notice that the coefficients of the panel and the quantile regression analysis are, in many instances, very different, especially when higher quantiles are considered. For some of the key variables (Input-IIT, INFL and VOL) these coefficients are also statistically different. This result underscores the importance of considering quantile regression analysis if one is interested in exploring the behavior of the upper tail of the distribution of persistence.

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

6. Conclusions

Using recent econometric results that show how the IR of the aggregate RER can be decomposed into those corresponding to its sectoral components, it has been argued that not all the sectors have the same importance in determining the persistence observed in the aggregate RER. Traditional theories of RER persistence (nontradability and nominal rigidities combined with pricing-to-market) have been investigated by means of quantile panel regression techniques. Our results suggest that persistence in the upper quantiles of sectoral persistence is explained by factors related to the stickiness of final goods prices and the market structure of their inputs. Since the behavior in the upper quantiles determine, to a large extent, the persistence observed at the aggregate level, it is concluded that pricing-to-market and price stickiness are two key factors in explaining the slow reversion to PPP of European RERs. Further research is needed to clarify whether these conclusions can be extended to other economic areas.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.jmoneco.2011.06.003.
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