

Global Versus Local Shocks in Micro Price Dynamics*

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Abstract

A number of recent papers point to the importance of distinguishing between the price reaction to micro and macro shocks in order to reconcile the volatility of individual prices with the observed persistence of aggregate inflation. We emphasize instead the importance of distinguishing between *global* and *local* shocks. We exploit a panel of 276 micro price levels collected on a semi-annual frequency from 1990 to 2010 across 88 cities in 59 countries around the world, that enables us to distinguish between *different* types (local and global) of *micro* and *macro* shocks. We find that global shocks have more persistent effects on prices as compared to local ones e.g. prices respond faster to local macro shocks than to global micro ones, implying that the relatively slow response of prices to macro shocks documented in recent studies comes from global rather than local sources. Global macro shocks have the most persistent effect on prices, with the majority of goods and locations sharing a single source of trend over time stemming from these shocks. Finally, both local macro and local micro shocks are associated with relatively fast price convergence.

Keywords: global shocks, local shocks, micro shocks, macro shocks, price adjustment, micro-macro gap, price-setting models, micro prices.

JEL Classification: E31, F4, C23

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1 Introduction

How fast do prices adjust to changes in economic conditions? The answer is crucial in assessing the real effects of nominal shocks, for instance. The literature provides conflicting answers: whereas aggregate price indices have been found to be very persistent, more recent work starting with Bils and Klenow (2004) showed that individual prices adjust frequently. The implication that monetary policy might as a result be less effective than previously thought, has been challenged more recently. Boivin et al. (2009) attempt to resolve the micro-macro puzzle while retaining the importance of monetary policy by distinguishing between the (sluggish) response of individual prices to *macroeconomic shocks* common to every sector or product, and their (rapid) response to *microeconomic shocks* specific to a sector or product. Our paper emphasizes the distinction between *global shocks* common to every location worldwide, and *local shocks* specific to a location. We show that this distinction is much more striking and no less informative for price-setting models, than the macro-micro split considered in previous work.¹

In fact, we find that the speed of price adjustment in response to local macro shocks or local micro shocks is relatively fast in both cases. At the same time, the price persistence associated with global versus local shocks of any type differs substantially. For both macro and micro shocks alike, local components are associated with much less persistence than global ones. Considering only one type of micro or macro shock would consequently hide the heterogeneity we observe in their effects and lead to misleading inferences about the relative persistence of local macro shocks (typically monetary ones) in micro prices. Based on our findings, price-setting theory models should not include as high a degree of price rigidity in response to local macro shocks as that implied in some of the earlier empirical work. At the same time, our work suggests the need for open economy price-setting theory models consistent with slow response of prices to global micro shocks and persistent price effects of international macro shocks.²

Our analysis relies on a panel of 276 micro price levels collected from 1990 to 2010 at a semi-annual frequency across 88 cities in 59 countries across the world. This dataset is non-standard and was especially compiled for us by the Economist Intelligence Unit (EIU) at a semiannual frequency

¹The implication that monetary policy might be less effective than previously thought as a result of frequent price adjustment, has also been challenged by Nakamura and Steinsson (2008) who attribute the Bils and Klenow (2004) finding to temporary sales-induced price reductions, and by Kehoe and Midrigan (2010) who allow for temporary sales in their model to propose that the aggregate price level is sticky and monetary policy effective even as micro prices change frequently. Our data is specifically designed to avoid sales so that our findings regarding the speed of price adjustment relate to standard rather than sale prices, and are not exposed to this critique.

²Kehoe and Midrigan (2007), Atkeson and Burstein (2008), Crucini et al. (2010), and Gopinath and Itskhoki (forthcoming) are some examples of open macro models that consider optimal price-setting and price dynamics. Our results suggest further emphasis on price-setting theory models in an open economy context would be useful to understand the different impact different types of international vs local shocks have on the speed of price adjustment.

for the complete untypically large sample of international locations.³ The March and September dates for gathering these semi-annual data are specifically designed to avoid standard sales seasons. In addition, EIU correspondents are specifically instructed to take regular retail prices and not to take sale prices. These sampling facts suggest that our price data are not as prone to include temporary price changes, shown by Nakamura and Steinsson (2008) to bias results towards finding more rapid price adjustment.⁴ This is important for the inferences we can draw about the speed of price adjustment in response to local shocks for instance.⁵

The three dimensions of our panel—time, location and individual product—allow us to decompose the dynamics of the common currency micro price-level⁶ for each product in a given location at a given date into four different components: (1) a *global macro* component common to every good in every location, capturing for example global oil shocks; (2) a *global micro* component specific to a good and common to every location, related for instance to technology shocks specific to a product but common across the globe; (3) a *local macro* component specific to a location and common to every good, related for example to monetary policy; and (4) a *local micro* or *idiosyncratic* component specific to a good and a location, capturing for instance the idiosyncrasy of weather conditions facing vineyards in a certain location. We obtain convergence rates specific to each component allowing for different speeds of price adjustment to these, our notion of price adjustment speed being the time it takes for prices to fully adjust to a shock.

While ignoring the global-local distinction our data would imply that (similar to past research on the micro-macro gap) macro shocks are more persistent than micro ones with convergence rate estimates implying half-lives of 21 months versus 13 months respectively, decomposing macro and micro shocks into their global and local components reveals a different more precise picture. Local

³The standard EIU city prices edition typically used in work that looks at convergence in LOP deviations, e.g. Crucini and Shintani (2008) or Zachariadis (forthcoming), is available only at the annual frequency. On the other hand, the semi-annual EIU city prices subset used in Bergin et al. (2011) ending in 2007, contains only 21 cities in 21 industrial countries.

⁴For example, De Graeve and Walentin (2011) use an approach that handles sale prices in the Boivin et al. (2010) data and find persistent micro shocks in contrast to the earlier paper.

⁵That our data is relatively free of temporary price changes presents an important advantage in this matter relative to datasets affected by sale prices. Moreover, our data has relatively low (semi-annual) frequency and again should not be dominated by high-frequency changes over the year. As pointed out by Kehoe and Midrigan (2010), what matters for how the aggregate price level responds to low-frequency changes in monetary policy is the degree of low-frequency micro price stickiness rather than high frequency variation associated with temporary price changes. In their setting, there are two reasons that the aggregate price level is sticky even though micro prices change frequently. First, temporary price changes are highly clustered in time so that they are less able to offset persistent changes in monetary policy i.e. a firm that changes its prices four times in a single month is less able to respond to persistent money supply changes than a firm that spreads these four changes over a year. Second, when a firm changes its price temporarily it can react to changes in monetary policy but these responses are short-lived, and as soon as the price returns to the old one it no longer reflects the monetary policy change.

⁶Converting prices to a common currency is necessary for comparability. We use the US dollar but note that results are not that different using the British Pound or the Japanese Yen as numeraire currencies.

micro shocks are the most rapidly corrected ones, followed by local macro shocks, and global micro shocks. More precisely, local micro shocks have a half-life estimate of about 7 months. The reaction to local macro shocks is somewhat more persistent with a half-life of 10 months, while global micro shocks have a half-life that is about twice as long at 18 months.⁷ The latter three components of international prices are mean-reverting on average, but this does not apply to all relative prices for all goods or locations.⁸ The response of prices to global macro shocks is found to be permanent so that international prices share this single global stochastic trend which is the main factor behind the observed drift in price levels.⁹ Furthermore, we find that the global macro and micro components together account for half of the time-series volatility in prices in this sample. The above findings taken together suggest that global shocks cannot be ignored when analyzing the sources of persistence and volatility of prices. Our results confirm that prices react differently to different types of shocks, but stress that sorting shocks by geographic distance (global vs local) leads to more striking differences than sorting shocks by mere economic distance (macro vs micro).

The observed differences in persistence of the different price components could stem from differences in the persistence of the shocks driving the processes associated with these components rather than from differences in the reaction of prices to these shocks. We thus investigate further by considering the link between persistence and volatility of the price components. If persistence of the shocks themselves was the main driver of the observed persistence in prices, then we would expect to see a positive relation between own persistence and volatility. The estimated link between these turns out to be either negative or statistically indistinguishable to zero. This leads us to infer that price adjustment to different types of conditions does not stem from the mere persistence of the shocks. The link between persistence and volatility provides us with a couple of additional new facts. First, more volatility in micro conditions is associated with slower adjustment of prices, hence more persistent relative price distortions, in response to changes in macro conditions. Likewise, more volatility in local conditions is associated with slower price adjustment, hence more persistent relative price distortions, in response to changes in global conditions, with this link more than twice as large as the respective micro-macro link.

We propose that decomposing macro and micro shocks into finer categories provides a new more precise tool for gauging models of price-setting. The persistence associated with each of these components and its relation with volatility of the different components, provide new facts that price-setting models should be able to rationalize. First, in light of the importance of the global or international dimension, it would be useful to have open economy price-setting models that can

⁷These mean reversion measures pertain to the average across goods or locations.

⁸Some of these relative prices are instead characterized by a specific stochastic trend as shown in Table 3.

⁹The absence of other stochastic trends in particular validates the theoretical assumption by Golosov & Lucas (2007) that goods relative prices within a location have no specific trend, ensuring that their time variance is bounded.

rationalize differences in the speed of adjustment to global versus local shocks in addition to macro versus micro shocks. These models should be able to explain why these differences are more striking when shocks are classified with respect to geographic distance (global vs local) rather than mere economic distance (macro vs micro). Second, models of price-setting should be able to cope with the estimated sign and size of the link between local volatility and the rate of price adjustment in response to global shocks.¹⁰ Again, they should also be able to explain why the volatility in local conditions seems to be more detrimental to the adjustment to global conditions, as compared to the effect of volatility in micro conditions for the adjustment to macro conditions.

One possibility would be to resort to models of endogenous imperfect perception of shocks, in the spirit of the recent contributions of Reis (2006), Maćkowiak and Wiederholt (2009), Woodford (2009) or Alvarez et al. (forthcoming), where the relative cost of observing global conditions would be greater than the one associated with monitoring local ones, and more so than the relative cost of observing macro conditions exceeds that for micro ones. Similarly, in the context of these models, the loss of processing capacities due to volatility in local conditions could be more detrimental to the monitoring of global conditions, as compared to the loss of processing capacities due to volatility in micro conditions for the monitoring of macro conditions. Rational inattention models are thus a natural candidate to consider for understanding our results. Yet another theoretical possibility would be to rely on labor market segmentation arguments, in the spirit of Carvalho and Lee (2010).¹¹ Here, the segmentation would need to be greater between countries than within them in the same manner (but more so) that labor segmentation is greater across sectors than within them. However, this framework would also need to incorporate a link between volatility of shocks and persistence of price reactions.

Our results on the differential response of prices to different types of shocks extend Clark (2006), Boivin et al. (2009), and Maćkowiak et al. (2009), to a global environment. These papers bridge the gap between measured persistence of macro price indices and the frequent adjustment observed in micro prices.¹² In their setup, a macro shock is common to every sector in the US, potentially encompassing a shock common to every country worldwide (our global macro shock) and a shock specific to the US (our local macro shock). Likewise, their sectoral shock can be made of a worldwide sectoral shock (our global micro shock) and a US sector-specific one (our local micro shock). Our work points to the importance of disentangling global and local components to understand price

¹⁰Maćkowiak et al. (2009) discuss how a similar link, between micro volatility and the persistence of the price reaction to macro shocks, can be used to dismiss a basic version of a Calvo price setting model.

¹¹Their mechanism relies on these along with sticky prices, pricing complementarities due to intermediate inputs, and endogenous monetary policy.

¹²They show that sectoral prices react rapidly to US sectoral shocks and sluggishly to US macro shocks, arguing that as the latter account for such a low share of sectoral price variance it is not surprising to observe sectoral prices that on average adjust rapidly. Altissimo et al. (2009) find similar results for the euro area.

dynamics. No study of micro price levels has looked at this global/local decomposition of micro and macro shocks.¹³ We show that whereas global macro shocks are highly persistent, prices react to local macro shocks much faster than to global micro ones. By contrast, Boivin et al. (2009) find that sectoral prices adjust sluggishly to macro shocks but rapidly to micro ones, a result that has in turn spurred a debate on what theoretical model of price-setting could rationalize such different response of individual prices to different types of shocks. In their own words, their “main finding is that disaggregated prices appear sticky in response to macroeconomic and monetary disturbances, but flexible in response to sector-specific shocks” and that “many prices fluctuate considerably in response to sector-specific shocks, but they respond only sluggishly to aggregate macroeconomic shocks such as monetary policy shocks”. To the extent that country-specific monetary policy is part of our local macro component, we find that it has much less persistent effects than in Boivin et al. (2009). Prices respond almost twice as fast to local macro shocks as they do to global micro ones. This also contrasts with the finding of a rapid adjustment to micro shocks in Boivin et al. (2009).

The subset of our results that pertains to local micro and local macro shocks contributes to yet another line of research; the literature on international price comparisons. Until recently, international price differences were considered to be very persistent at the aggregate level. Deviations from PPP have a half-life of several years as documented in the surveys by Rogoff (1996) and Obstfeld and Rogoff (2000). The survey by Goldberg and Knetter (1997) stresses that the persistence is of comparable order when one considers deviations from the LOP using relatively aggregated sectoral price indices. Instead, the recent evidence relying on micro-data, such as Goldberg and Verboven (2005) using European car prices, Crucini and Shintani (2008) using annual EIU prices, and Broda and Weinstein (2008) or Burstein and Jaimovich (2009) using barcode prices, is that the persistence of LOP deviations is reduced sharply when based on micro prices with higher comparability across locations. Our estimated half-lives are even lower than in the recent micro-price literature on LOP deviations, in part due to the use of semiannual prices and a broader sample of locations across the world as compared to the previous studies.

Although the scope of our paper is broader, to the extent that a subset of our results relates to the LOP literature discussed above they are also relevant for the Bergin et al. (2011) argument that the differential importance and persistence of (local) macro versus (local) micro shocks for LOP deviations can reconcile the macro with the micro evidence for international price convergence rates

¹³Using sectoral price indices, Beck et al. (2010) also emphasize the variance of geographical components as an important part of what was previously thought to be micro shocks. The related literature on global shocks has found a large common component in international aggregate inflation indices in OECD countries (Ciccarelli & Mojon, 2010) or in disaggregated inflation at the CPI product level in OECD countries (Monacelli & Sala, 2008). As compared to these, we use a large number of micro-prices and global locations to further decompose the common component into macro and micro global components, stressing that the micro part accounts for a greater share of in-sample variance.

estimates.¹⁴ They show that macro shocks that dominate at the aggregate level are less volatile and have much greater persistence than idiosyncratic shocks at the individual good level that dominate micro prices. We estimate a more persistent response of individual prices to local macro shocks than to idiosyncratic ones in most cases.¹⁵ However, both responses are relatively fast and not always that different except for developed countries. Thus, our results suggest that the micro/macro gap between fast convergence in deviations from the LOP (micro) and the very persistent deviations from PPP (macro) cannot be entirely resolved by distinguishing between (local) macro and (local) micro shocks in the LOP as there is typically not that much more persistence in local macro shocks as compared to local micro ones. Apart from the much more general sample across (developed and developing) countries and goods (traded and non-traded), and the longer time span being considered in our paper, one factor driving differences in estimates for the local micro and local macro components in the two papers, is that Bergin et al. (2011) use the US as the comparison point relative to which to construct LOP deviations. Choosing a particular location as the comparison point introduces the statistical properties characterizing it into the deviations from the LOP for every other location.¹⁶ Instead, we choose to compare prices to the average across locations so that our findings do not depend on choosing a particular country as the comparison point.

Finally, our findings do not depend on using the US dollar as the numeraire currency. Converting prices to the same currency is necessary for comparison. However, as discussed in section 3, conversion to the same numeraire currency introduces to some of the price components (i) the external adjustment to shocks via the exchange rate, and (ii) shocks specific to the reference currency country. If these dominated the internal adjustment of domestic prices to various shocks, estimation of the speed of price adjustment to different types of shocks would not be robust to the choice of reference currency. We show this is not the case. Results regarding the non-stationarity of the global macro component or the speed of adjustment to the global micro or to any of the local components are, overall, not that different when we consider the British Pound or the Yen.

Next, we describe the data. We then present our statistical model. Following that, we discuss our results, and then proceed to explain price persistence of the different components with volatility of shocks and a set of controls to further link our findings to theory. The final section concludes.

¹⁴Imbs *et al.* (2005) argue instead that the gap between fast adjustment of LOP deviations and the slow adjustment of aggregate indices in the PPP literature comes from aggregating heterogeneous sectoral price dynamics. Carvalho and Nechio (2008) propose an aggregation effect arising in a multi-sector two-country model with heterogeneity in the degree of price stickiness across sectors that leads to heterogeneous dynamics in sectoral real exchange rates.

¹⁵Non-traded is an exception with identical adjustment speed in response to macro and micro local shocks.

¹⁶For example, their result does not hold with Germany, France or the UK as the comparison point.

2 Data

2.1 Description and reliability

The main source of data utilized in our application comes from the Economist Intelligence Unit (EIU). EIU prices were provided to us for 327 items in 140 cities in 90 countries twice a year, where available, from 1990 to 2010. The semiannual (March and September) prices were especially compiled for us by the EIU upon request, as the standard historical data in the EIU “cityprices” publication contains prices gathered only once a year, every September. In the data appendix, we undertake a detailed description of how these prices are collected and put together, meant to help the reader understand the potential advantages and disadvantages of using this dataset to study international prices and to assist future users in appropriately handling these data. Although subsamples of these data have been used previously as described below, the information provided in the data appendix is largely new.

For example, the data appendix sub-section on “Sampling, seasonality, and sales”, describes how the March and September dates for gathering data were specifically designed to avoid standard sales seasons, like traditional sales in December, January, May and June which take place in many countries, and that furthermore, correspondents are instructed not to take sale prices but to take standard recommended retail prices. This is an important dimension over which this dataset has an advantage over other price datasets ridden with sale prices that tend to bias estimates towards faster speeds of adjustment while being less suited to assessing the effectiveness of monetary policy.

Engel and Rogers (2004), Crucini et al. (2004), Bergin and Glick (2007), Crucini and Shintani (2008), Crucini and Yilmazkuday (2009), Bergin et al. (2011), and Zachariadis (forthcoming) have all exploited sub-samples of these EIU prices. The first paper focuses on a sample of prices in 18 European cities for 101 traded and 38 non-traded products for the period from 1990 to 2003, to ask how much more integrated the EU has become after the introduction of the euro. The second utilizes the EIU data averaged over the period from 1990 to 2000, focusing on the first and second moments of the cross-sectional distribution of bilateral country prices across goods, to assign a role to geographic variables. Bergin and Glick (2007) focus on a sample of 101 tradeable goods in 108 cities in 70 countries for the period from 1990 to 2005, to assess global price convergence. Crucini and Shintani (2008) focus on a sample of 90 cities in 63 countries for the period from 1990 to 2005, to assess the rate of price convergence for the relative price of each good. Crucini and Yilmazkuday (2009) average prices over 1990-2005 and explain this cross-sectional dimension with trade and distribution costs. Bergin et. al. (2011) study a subset of these data for traded goods price comparisons between the US and 20 cities in 20 industrial countries at a semiannual

frequency from 1990 to 2007 in an attempt to resolve the macro-micro disconnect of PPP and the LOP. Finally, Zachariadis (forthcoming) exploits the annual EIU price data for as many as 19 countries for 1990-2006 to investigate the role of international movements of labor in narrowing the gap for LOP deviations across countries.

As compared to the above papers, we have access to semiannual prices for 1990 to 2010 for the great majority of locations. Restricting the sample to goods and locations always present during this period, we end up with price levels for 276 goods and services across 88 cities in 59 countries. Table 1 provides a complete list of goods and locations (cities and countries) present in our sample. It also provides a classification between less developed countries (LDC) with income per capita less than \$12,000 and more developed countries (DEV) in our sample,¹⁷ and a classification of goods between traded (TR) and non-traded (NT). We note that there is a much lower number of NT items available as compared to TR products and a lower number of LDC locations. Most traded goods prices are observed in two types of stores, so that we end up with two price observations per date and location for 100 goods. In Table 1, we also report the type of store (supermarkets, chains, and mid-price or brand stores) each good was sampled in.

For some of our results, we focus on a restricted sample of 49 countries, excluding EMU countries other than Germany, to address the fact that EMU countries do not undertake independent monetary policy so that local macro shocks would not be as related to monetary policy if these were included. Similarly, we have restricted our main analysis to countries rather than cities since the latter cannot undertake independent monetary policy. However, we also consider a more complete sample of 59 countries including EMU ones, as well as a city-level analysis for 88 cities in these 59 country sample.

All prices are converted in a common currency, the US dollar, using exchange rate data assembled by the EIU to match the sampling periods of the city price levels data. We also used the US dollar exchange rates to reconstruct exchange rate data for the British Pound and Yen relative to the national currencies of the locations in the sample, in order to consider the robustness of the results to the numeraire currency. We obtained PPP-adjusted real GDP per worker from the Penn World Tables (up to 2007) and country-level population from the World Development Indicators.

¹⁷Our classification of less developed countries is based on the PPP adjusted GDP per capita from the Penn World Tables. These are countries with income per capita below \$12000 on average over 1990-2007. This threshold corresponds to the average income per capita in the cross country distribution of the Penn World sample.

2.2 Descriptive statistics

The EIU city price data include vastly different priced items. Some summary statistics regarding these EIU prices are presented in Table 2. There are much more cross-sectional differences, with a standard deviation equal to 2.57, as compared to time fluctuations that have a standard deviation of 0.33. The distribution of prices is skewed to the right, i.e. the distribution mass is more concentrated on small values. The autocorrelation coefficient averages around 0.81, implying persistent effects of shocks.

Moreover, we observe that more developed countries have higher price levels, less heterogeneity in each dimension, lower volatility, and more persistent effects of shocks. At the same time, traded goods in this sample have lower price levels on average than non-traded ones, as well as less heterogeneity in each dimension except for the speed of convergence. Traded goods are also characterized by comparable volatility with non-traded goods, and by less persistent effects of shocks on prices. The above suggest the absence of a systematic link between volatility and the speed of price convergence. That is, while more volatility in LDCs is associated with more rapid convergence, lower convergence for non-traded goods coexists along with similar degrees of volatility for traded and non-traded goods. A potential explanation for this might be that goods characteristics interact with location (city/country) characteristics so that prices react differently to these different components. We consider this decomposition in the following section.

3 A statistical model of goods prices in different locations

3.1 Price components and relative prices

Let p_{ilt} be the common currency (log) price of good item i in location l at date t . We consider a decomposition of international prices into four components, namely

$$p_{ilt} = \alpha_{il}m_t + \beta_i m_{lt} + \gamma_l m_{it} + m_{ilt}.$$

The term m_t represents a component affecting *every price in every location*. We refer to this as the *global macroeconomic* component of prices. A typical example of a global macro component would be oil prices. Changes in oil prices have different impact on prices depending on the location considered, for instance because of the distance to production, or on the goods considered, for instance because of the composition of intermediate inputs. Such heterogeneity in price reactions is captured by the heterogeneity in the parameter α_{il} .

The second term, m_{lt} , denotes a component affecting the price of *every good for a given location*. We refer to this as the *local macroeconomic* component of international prices, typically monetary or fiscal policies. An aggregate demand shock specific to a location can induce different reaction in prices of different goods, according to markup determinants such as demand elasticities or the cost of updating prices. We allow for such heterogeneous reaction of prices by allowing for heterogeneity in the parameter β_i . We could consider that the reaction of prices to local macro shocks differs according to both goods and locations. In that case, the effect of the local macroeconomic component on international prices would be described by a term $\tilde{\beta}_{il}\tilde{m}_{lt}$. However, this turns out to be only a matter of normalization if we assume that one can separate the total impact between its location and good-specific components. For instance, if $\beta_{il} = \beta_i\beta_l$, one can rewrite such a term as $\beta_i m_{lt}$ with $m_{lt} = \beta_l \tilde{m}_{lt}$.

The third term, m_{it} , represents a component affecting the price of *a given good in every location*. We refer to this as the *global microeconomic* component of international prices. A natural example would be an innovation specific to a given product. Such innovations can have a different impact on prices depending on the location to which the product is sold, typically due to the distance to the innovation frontier of the specific location considered. Such potential differences are captured in the heterogeneity of the parameters γ_l . As underlined in the previous paragraph, the heterogeneity of the reaction allowed for in our model encompasses the broader case where $\tilde{\gamma}_{il}\tilde{m}_{it}$ with $\tilde{\gamma}_{il} = \gamma_l\gamma_i$.

Lastly, the residual term, m_{ilt} , captures the component affecting the price of *a given good in a given location*. We refer to this as the *local microeconomic* or idiosyncratic component of prices. A typical example of a factor affecting this component would be a strike in a given sector and location.

Our identifying assumptions allow us to estimate each component from observed prices by applying simple average and difference transformations. We assume that each of these underlying components can be described by auto-regressive univariate processes so that

$$m_{*t} = c_* + \delta_*(L)m_{*t-1} + \epsilon_{*t},$$

where $* = \{\emptyset\}$, i , l or il , the terms ϵ represent mutually independent white noise processes, and the operators $\delta(L)$ are polynomials in the lag operator satisfying standard invertibility conditions. The dynamics of prices are thus given by

$$p_{ilt} = \mu_{il} + \rho_{il}(L; m)m_{t-1} + \rho_{il}(L; m_l)m_{lt-1} + \rho_{il}(L; m_l)m_{lt-1} + \rho_{il}(L; m_i)m_{ilt-1} + \varepsilon_{ilt} \quad (1)$$

with $\mu_{il} = \alpha_{il}c + \beta_i c_l + \gamma_l c_i + c_{il}$, $\rho_{il}(L; m) = \alpha_{il}\delta(L)$, $\rho_{il}(L; m_l) = \beta_l\delta_l(L)$, $\rho_{il}(L; m_i) = \gamma_l\delta_i(L)$, $\rho_{il}(L; m_{il}) = \delta_{il}(L)$, and $\varepsilon_{ilt} = \epsilon_t + \epsilon_{lt} + \epsilon_{it} + \epsilon_{ilt}$.

Lastly, we make two types of normalization assumptions. First, we assume that location-specific components average out across locations and that good-specific components average out across

goods. More precisely, letting $E_z(x_{yz}|y)$ denote the expectation of x_{yz} conditional on y and over all possible values of z , we postulate that $E_l(m_{it}|t) = E_l(m_{ilt}|it) = 0$ and $E_i(m_{it}|t) = E_i(m_{ilt}|lt) = 0$. This obviously also implies that $E_{il}(m_{ilt}|t) = 0$. Second, as the coefficients α_{il} , β_i and γ_l give the impact of each component for a given good in a specific location relative to the average, we normalize this average reaction to unity, namely $E_{il}(\alpha_{il}) = E_i(\beta_i) = E_l(\gamma_l) = 1$.

Our model structure has some implications for two important measures of relative prices. First, the so-called deviations from the law of one price (LOP) widely discussed in the international economics literature, i.e. the price of a given good in a given location relative to the price of the same good in other locations. Letting $\bar{p}_{it} = \frac{1}{n_{li}} \sum_l p_{ilt}$, with n_{li} the number of locations for which good i is sampled, deviations from the LOP are given as

$$q_{ilt} = p_{ilt} - \bar{p}_{it},$$

and under the assumptions of our econometric model, converge to a process given by

$$q_{ilt} = \beta_i m_{it} + m_{ilt} + u_{ilt},$$

with $u_{ilt} = (\alpha_{il} - \bar{\alpha}_i)m_t + (\gamma_l - 1)m_{it} + \{\bar{p}_{it} - E_l(p_{ilt}|it)\}$ and $\bar{\alpha}_i = E_l(\alpha_{il}|i)$. The relative price for a given good in a given location compared to other locations is therefore the combination of a common location-specific component, a good-location idiosyncratic term, and a residual resulting from the specific contribution of the global (both macro and micro) shocks to the price of that specific good in that specific location and an in-sample estimation error.

Our model structure also has implications for a second important measure of relative prices, pertaining to deviations from “pure inflation”¹⁸ within a country, i.e. the price of a given good in a given location relative to other goods in the same location. Letting $\bar{p}_{lt} = \frac{1}{n_{il}} \sum_i p_{ilt}$, with n_{il} the number of goods sampled in location l , this relative price is given by

$$r_{ilt} = p_{ilt} - \bar{p}_{lt},$$

which, under our model’s assumptions converges to a process described by

$$r_{ilt} = \gamma_l m_{it} + m_{ilt} + v_{ilt},$$

with $v_{ilt} = (\alpha_{il} - \bar{\alpha}_l)m_t + (\beta_i - 1)m_{it} + \{\bar{p}_{lt} - E_i(p_{ilt}|lt)\}$ and $\bar{\alpha}_l = E_i(\alpha_{il}|l)$. The relative price for a given good in a given location compared to other goods is therefore the combination of a common good-specific component, a good-location idiosyncratic term, and a residual resulting from the

¹⁸In the terminology of Reis and Watson (2009), “pure inflation” is the variation in prices that is common to every good in a given country so that it leaves relative prices constant.

specific contribution of the macro (both global and local) shocks to the price of that specific good in that specific location and an in-sample estimation error.

The price components m_t , m_{lt} , m_{it} , and m_{ilt} that appear in the dynamics of the last two relative prices are not directly observable. However, the model structure allows us to approximate them by linear combinations of the averages over the different indices. Indeed, letting $\bar{p}_t = \frac{1}{n} \sum_{il} p_{ilt}$, with $n = \sum_i n_{i|l} (= \sum_l n_{l|i})$ the number of individual units in the sample, $\bar{q}_{lt} = \frac{1}{n_{i|l}} \sum_i q_{ilt}$, and $\bar{r}_{it} = \frac{1}{n_{i|i}} \sum_{il} r_{ilt}$, then one can show that

$$\bar{p}_t \rightarrow m_t, \quad \bar{q}_{lt} = (\bar{p}_{lt} - \bar{p}_t) \rightarrow m_{lt} + (\bar{\alpha}_l - 1)m_t, \quad \text{and} \quad \bar{r}_{it} = (\bar{p}_{it} - \bar{p}_t) \rightarrow m_{it} + (\bar{\alpha}_i - 1)m_t,$$

where \rightarrow stands for convergence in probability. So m_{lt} can be estimated by projecting \bar{q}_{lt} over \bar{p}_t . Likewise, m_{it} can be estimated by projecting \bar{r}_{it} over \bar{p}_t . As a consequence, consistent estimates of the price dynamics properties can be obtained by resorting to the following regressions

$$\bar{p}_t = \nu + \rho(L)\bar{p}_{t-1} + \eta_t, \tag{2}$$

$$q_{ilt} = \nu_{il}^q + \bar{\rho}_{il}^q(L)\bar{q}_{lt-1} + \tilde{\rho}_{il}^q(L)(q_{ilt-1} - \bar{q}_{lt-1}) + \phi_{il}^q \bar{p}_t + \psi_{il}^q \bar{r}_{it} + \eta_{ilt}^q, \tag{3}$$

$$r_{ilt} = \nu_{il}^r + \bar{\rho}_{il}^r(L)\bar{r}_{it-1} + \tilde{\rho}_{il}^r(L)(r_{ilt-1} - \bar{r}_{it-1}) + \phi_{il}^r \bar{p}_t + \psi_{il}^r \bar{q}_{lt} + \eta_{ilt}^r. \tag{4}$$

Indeed, it follows from the previous analysis that $\rho(L) \rightarrow E_{il}\rho_{il}(L; m_l)$, $\bar{\rho}_{il}^q(L) \rightarrow \rho_{il}(L; m_l)$, $\tilde{\rho}_{il}^q(L) \rightarrow \rho_{il}(L; m_i)$, $\bar{\rho}_{il}^r(L) \rightarrow \rho_{il}(L; m_i)$, $\tilde{\rho}_{il}^r(L) \rightarrow \rho_{il}(L; m_{il})$, where $\rho_{il}(L; m_*)$ are the polynomials defined in equation (1), with $*$ being either $\{\emptyset\}$, i , l , or il .

3.2 Discussion

Converting prices to the same currency is necessary for comparability, but implies that the adjustment to shocks thus captured is a combination of the internal adjustment of domestic prices and the external adjustment through the exchange rate. We discuss how this choice might affect the estimation of the price components and how one can circumvent the problem.

Interestingly, this external adjustment does not show up in every relative price we consider. More precisely, let p_{ilt}^* be the local currency (log) price of good i in location l and s_{lt} be the (log) exchange rate of the local currency into the chosen reference currency. By definition the good-specific relative prices do not depend on the reference currency since

$$r_{ilt} = (p_{ilt}^* + s_{lt}) - \frac{1}{n_{i|l}} \sum_i (p_{ilt}^* + s_{lt}) = p_{ilt}^* - \frac{1}{n_{i|l}} \sum_i p_{ilt}^*$$

and hence $\bar{r}_{it} = \frac{1}{n_{i|i}} \sum_i r_{ilt} = \frac{1}{n_{i|i}} \left(\sum_i p_{ilt}^* - \frac{1}{n_{i|i}} \sum_i p_{ilt}^* \right)$. On the contrary, the location-specific

relative prices do depend on the reference currency since

$$q_{ilt} = (p_{ilt}^* + s_{lt}) - \frac{1}{n_{l|i}} \sum_l (p_{ilt}^* + s_{lt}) = \left(p_{ilt}^* - \frac{1}{n_{l|i}} \sum_l p_{ilt}^* \right) + \left(s_{lt} - \frac{1}{n_{l|i}} \sum_l s_{lt} \right)$$

and $\bar{q}_{lt} = \frac{1}{n_{i|l}} \sum_i q_{ilt} = \left[\frac{1}{n_{i|l}} \sum_i \left(p_{ilt}^* - \frac{1}{n_{l|i}} \sum_l p_{ilt}^* \right) \right] + \left(s_{lt} - \frac{1}{n_{l|i}} \sum_l s_{lt} \right)$. The impact of the external adjustment through the exchange rate increases with the extent to which the location-specific exchange rate, s_{lt} , has a specific dynamic compared to the average one, $\frac{1}{n_{l|i}} \sum_l s_{lt}$. However, on average, these idiosyncrasies in exchange rate dynamics cancel out. Consequently, taking the average of the location-specific speeds of convergence to local shocks will give us an estimate of the average reaction of prices to local shocks due to the mere internal adjustment mechanism.

The global price average can be written as

$$\bar{p}_t = \frac{1}{n} \sum_{il} (p_{ilt}^* + s_{lt}) = \bar{p}_t^* + \bar{s}_t$$

It is thus a combination of factors that affect local currency prices everywhere, and factors that have an effect on the exchange rate of the numeraire currency relative to other currencies. Put it differently, aside to local price reaction to global shocks, this price component captures the exchange rate reaction to shocks that are specific to the country of the numeraire currency. If this second component dominates in the global price average, then this would severely affect the estimation of price components other than the global one, as this global price average \bar{p}_t is necessary to recover them from the two relative prices q_{ilt} and r_{ilt} .

In the empirical analysis we start by using the US dollar as the numeraire currency. So, aside to global shocks affecting local prices everywhere, the global component is affected by shocks that are specific to the dollar, for instance US monetary policy shocks. This a natural choice to make: given the key role of the US dollar in international transactions, shocks that affect the dollar exchange rate worldwide can be considered as global shocks. However, we also check that this particular choice of the reference currency, hence US specific shocks, does not drive our results regarding the dynamics of the different price components, by considering other numeraire currencies.

To conclude this section, it is worth characterizing the type of bias induced by a split between the reaction of prices to macro and micro factors under the assumptions of our model. Because of data limitations, previous work, including Boivin et al. (2009), consider a price model of the following kind

$$p_{ilt} = \alpha_{il} f_{lt} + e_{ilt}.$$

Our postulated model structure gives insights on the type of bias this specification might imply. Indeed, a mapping between this model and our setup can be done by considering the macro component $f_{lt} = m_t + m_{lt}$ which obviously mixes the global and local macro components. The micro

component is then given by $e_{ilt} = (\beta_i - \alpha_{il})m_{lt} + \gamma_l m_{it} + m_{ilt}$ and therefore mixes the global and local micro as well as the local macro components. Whenever the different components have different time-series properties, e.g. different persistence parameters, the macro/micro split will thus lead to biased estimates of these parameters.

4 Estimation results

4.1 Stationarity tests of components

For the global macro component of prices, m_t , we conduct a standard ADF unit-root test using a standard auto-regression of \bar{p}_t . For the other components, m_{lt} , m_{it} , and m_{ilt} , we implement the cross-sectional ADF (CADF) unit-root testing procedure of Pesaran (2007). We rely on individual auto-regressions of respectively, \bar{q}_{lt} , \bar{r}_{it} , and q_{ilt} or r_{ilt} , and calculate averages of individual ADF test statistics. However, as equations (3) and (4) make clear, these individual auto-regressions are correlated across units because of the common factors \bar{p}_t , \bar{q}_{lt} , and \bar{r}_{it} . We thus follow Pesaran (2007) and control for these common factors directly in these test regressions.

As shown in Table 3, the only stochastic trend is in the average price level. That is, global macro shocks constitute the single source of non-stationarity. Relative prices are stationary on average. As we can see in Table 3, deviations from the LOP are stationary at the location level, i.e. taking the average across goods, for 62 out of 88 locations, as well as at the individual product-location level for 85 out of 88 locations. Similarly, relative prices within a location are stationary both at the product level, i.e. taking the average across locations, for 183 out of 276 goods, and at the individual product-location level for 271 out of 276 goods.

The latter finding of stationarity in relative prices within a country differs from the finding of stochastic trends in relative sectoral prices within a country in Boivin et al. (2009) or Maćkowiak et al. (2009). That relative prices are found to be stationary on average is important for the calibration of price-setting models. Our finding is consistent with the assumption of stationary idiosyncratic shocks in the theoretical price-setting model of Golosov and Lucas (2007). By contrast Gertler and Leahy (2008) assume non-stationary idiosyncratic productivity shocks.¹⁹

We note that we also find stationarity in the deviations from the LOP, confirming Crucini and Shintani (2008). As compared to the latter study, we use higher frequency (semiannual) and more recent (ending in year 2010 rather than 2005) data, and a modeling setup that allows for more

¹⁹We checked that these results are unchanged when using alternative numeraire currencies such as the Japanese Yen or the Sterling pound.

heterogeneity across goods and locations. We also note that we find stationarity for the subset of non-traded goods, whereas Bergin et al. (2011) find stationarity only for traded goods in their sample of 21 locations with semiannual data extending to 2007.

4.2 Persistence of components

We now turn to the estimation of the persistence characterizing each of the components that are on average stationary. In Table 4, we report a measure of persistence estimates, namely the sum of the coefficients characterizing the dynamics of each of the stationary components, m_{lt} , m_{it} , and m_{ilt} . More specifically, using the notation from equation (1) in section 3, Table 4 gives estimates of $\rho_{il}(1; m_*)$ with $*$ being either i , l or il . We also report the half-life associated with each of these persistence parameters, namely the time it takes to correct half of the initial shock.

Estimates are obtained through the common correlated effect mean-group (CCEMG) estimation procedure proposed in Pesaran (2006). This involves estimating the individual auto-regressive equations (3) and (4) and then averaging the individual parameter estimates. The inclusion of the common factors, \bar{p}_t , \bar{q}_{lt} , and \bar{r}_{it} , in the individual auto-regressions, (3) and (4), allows to get rid of the correlation across individual regression errors that these common terms would otherwise imply.

For the results reported in Table 4, we have restricted the analysis to countries rather than cities for comparability to previous literature investigating macro shocks at the national level. For example, monetary policy is typically undertaken at the national rather than city level. Moreover, we treat the EMU as a single entity since EMU nations do not undertake independent monetary action. Thus, we restrict our sample to 49 countries, capturing the EMU entity by Germany.²⁰ Even though we do not exactly identify monetary policy shocks, excluding locations that do not exercise independent monetary policy ensures that our local macro shocks will be more closely related to monetary shocks than otherwise. We also consider the robustness of our findings for a more complete sample of 59 countries including all EMU nations, as well as a city-level analysis that exploits the full dimension of our dataset across 88 cities in Table 5.

As we can see in Table 4, prices react differently to different types of shocks. The response to local macro shocks in the first column of Table 4 is relatively fast with a mean reversion rate of about 10 months which is higher than the convergence rate of 7 months for local micro shocks, but faster than the convergence rate of prices in response to global micro shocks which is around 18 months long.²¹ By contrast, as we saw in the previous section, the response of prices to global

²⁰Considering an average over EMU nations rather than capturing the EMU entity using Germany, does not affect our results.

²¹We note that a sample of homogeneous goods that are more highly comparable across countries, as explained in

macro shocks is permanent. It is important to note that the persistence parameters of the various components in international prices differ significantly from each other. Moreover, we note that there is a substantial amount of heterogeneity of the persistence parameters across goods and locations. We analyze some of its determinants in the next section.

The fact that global macro and global micro shocks have more persistent effects on prices than local ones is consistent with agents paying less attention to more distant shocks, not because they are macro rather than micro but because they are global rather than local. This is new and goes beyond the micro-macro distinction in Boivin et al. (2009) or Maćkowiak et al. (2009). In fact, abstracting from the global-local distinction, we find that macro shocks are more persistent than micro ones with associated respective convergence rates of 21 months versus 13 months as shown in the last couple of rows of Table 4, consistent with previous work on the micro-macro gap. Our results suggest that the global versus local distinction is crucial in order to uncover the reaction of prices to different types of shocks. For instance, our estimates show that prices are not that flexible in response to global micro shocks. Moreover, such micro shocks are in fact associated with slower price adjustment than local macro shocks that account for the effects of monetary policy.

Furthermore, the result that both local macro and local micro shocks are associated with relatively fast price convergence rates and not always that different from each other, even as local macro shocks typically have a somewhat more persistent effect on prices as compared to local micro ones,²² differs from and conditions the main result in Bergin et al. (2011). In the latter paper, local macro shocks are much more persistent than local micro shocks for a subsample of the locations and goods considered here, and that finding is used to explain the micro-macro gap that arises due to the fast adjustment of micro-LOP deviations responding mostly to micro shocks as compared to the persistence of PPP aggregates responding mostly to macro shocks. As we report in the next paragraph, differences in the sample of countries considered partly explain the difference in results, with Bergin et al. (2011) putting emphasis on developed economies and traded goods, while we study a broader sample spanning both developed and less developed countries and traded as well as non-traded goods and services. We have also checked that another and somehow more crucial reason for these differences is due to their use of the US as the comparison point relative to which they construct LOP deviations. Choosing one particular location as a comparison point introduces the statistical properties characterizing that location into the deviations from the LOP for every other location, which is one reason why we prefer to compare prices to the average across locations

the data appendix, gives similar results to those reported in Table 3 with half-lives of 16 months for global micro shocks, 11 months for local macro shocks, and 7 months for local micro ones.

²²As we will see below, non-traded goods being the exception in that local macro and local micro shocks have identical persistence in that case, and developed countries being the exception for the opposite reason i.e. that local macro shocks are much more persistent than local micro shocks in this case.

so that our findings do not depend on the use of one or another country. For example, using the exact same sample of goods and locations as in Bergin et al. (2011) while using Germany, France or the UK rather than the US as the comparison point, does not give their main result about the relative persistence of prices in response to macro shocks.

The reaction to the shocks differs depending on goods' characteristics and the country's development level. As we show in Table 4, both global as well as local micro shocks are more rapidly corrected for traded as compared to non-traded goods, and the same goes (to a lesser extent) for local macro shocks. Moreover, the reaction to global micro shocks is clearly slower in the less developed countries in our sample. By contrast, both local macro and local micro shocks are more rapidly corrected in less developed countries as compared to more developed ones. The latter findings suggests that LOP/PPP studies (focusing by construction on local components) that consider rich economies might infer a higher degree of persistence than is actually the case in the global sample of locations we consider.²³

Robustness of persistence estimates

We consider a number of robustness checks and report results in Table 5. First, we consider the complete sample of countries as compared to the restricted sample that treated Euro area countries as a single entity, results for which were reported in Table 4. Persistence estimates of prices in response to the different types of shocks and their relative ranking remain quantitatively and qualitatively the same to those in Table 4. As we can see in column (1) of Table 5, half-lives associated with the response of prices to local macro and local micro shocks remain at 10 and 7 months respectively. The half-life associated with the response of prices to global micro shocks is now 20 months, compared to 18 months for the restricted sample in column (1) of Table 4.

Second, we consider the issue of converting prices to a common currency other than the US dollar. More specifically, in columns (2) and (3) of Table 5 we consider the conversion of local currency prices into British Pound and Yen prices respectively. As we can see in column (2) of Table 5 using the British Pound, the half-life of the price adjustment in response to global micro shocks is now up to about two years. The half-life of the price adjustment in response to local micro shocks is now up to 8 months, very close to the half-life of 9 months for local macro shocks. Results using the Japanese Yen reported in column (3) of Table 5 suggest a half-life of 26 months in response to global micro shocks, 9 months for local micro shocks, and 10 months for local macro shocks. Overall, the ranking in terms of the relative persistence of prices in response to global micro, local macro, and local micro shocks does not change. However, price adjustment in response to global micro shocks

²³The finding of faster convergence for LOP deviations among less developed countries is consistent with the opportunity cost of time and search costs that are lower in poorer countries as in Alessandria and Kaboski (2010).

reported in columns (2) and (3) of Table 5 is even slower than what was obtained using US dollar prices. Moreover, local micro shocks are now associated with somewhat slower speed of adjustment than was the case using US dollar prices. In fact, the speed of price adjustment in response to either local macro or local micro shocks is now very similar and differs only by a month.

The EIU samples only one price per good per type of store in a given city and period, which could lead to measurement error if this single price is used as the basic unit of analysis. To alleviate this source of measurement error, we now average prices across types of stores for a given good, city, and time period, which is possible since prices are available for two types of stores for most goods as shown in Table (1). In column (4) of Table 5, we report persistence estimates that utilize this average price as the basic unit of analysis. As we can see, this exercise confirms our original results. The half-lives associated with the local macro, local micro and global micro shocks are 10, 8, and 21 months respectively as compared to the equal or lower respective values of 10, 7, and 20 months reported in column (1).

Finally, we consider city-level analysis for the complete sample of locations, exploiting the full spatial dimension of our dataset across 88 cities. If this gives results similar to the country-level analysis, it would suggest that the response of prices in individual cities is driven by nationwide shocks like monetary policy ones that dominate any city-level shocks. In column (5) of Table 5, we show that global micro shocks are now associated with a half-life of 17 months as compared to about 20 months for the country-level analysis in column (1) of the table. This is due to the fact that the city-level sample is tilted to developed countries for which the adjustment to global micro shocks is more rapid than average. Other than this sample-induced difference, half-lives are very similar. Local macro shocks are now associated with a price response of 11 as compared to 10 months for the country-level analysis in column (1), and local micro shocks associated with a half-life of 7 months in both columns (5) and (1) of the Table. Once again, the relative ranking of persistence estimates of prices in response to the different types of shocks remains the same.

4.3 Time variance of components

We now turn to the time-series variance associated with the different components in order to begin to understand the sources of price volatility in this sample of goods and locations for the period from 1990 to 2010 at the semiannual frequency. More specifically, let $V(x_{yzt}|yz)$ denote the time variance of x_{yzt} , Table 6 reports a decomposition of the average time-variance of prices $E_{il}\{V(p_{ilt}|il)\}$, into its four components: the average time-variance of global, location specific, good specific, and good-location idiosyncratic components of prices. We estimate each of these four variances by, respectively, $V(\bar{p}_t)$, $E_t\{V(\bar{q}_{lt}|l)\}$, $E_i\{V(\bar{r}_{it}|i)\}$ and $E_{il}\{V(p_{ilt} - \bar{p}_t - \bar{q}_{lt} - \bar{r}_{it}|il)\}$.

As we can see in Table 6, global shocks account on average for half of the time-series fluctuations of prices. In particular, global micro shocks account for almost forty percent of these fluctuations. Moreover, as we can see in Table 6 local micro shocks are more volatile than local macro shocks consistent with Boivin et al. (2009).

Considering different types of goods, we find that non-traded goods are associated with more volatile global micro shocks than traded goods. Moreover, less developed countries in our sample have more volatile local shocks. This is especially the case for local macro shocks exhibiting five times as much volatility in less developed countries than in more developed ones, perhaps due to the relative stability of monetary policy in the latter group of countries. Less developed countries also exhibit twice as much volatility than more developed ones, in response to local micro shocks. This is perhaps due to the relative instability and higher degree of uncertainty facing particular markets in these countries, with shortages and sudden shifts in demand and supply a more common phenomenon in less developed economies where markets do not typically operate as smoothly.

5 Cross-section determinants of price persistence

Are global components of prices more persistent than local ones because global shocks are intrinsically more persistent than local ones, or because prices adjust at different speeds in response to changes in global and local conditions? Moreover, do more volatile economic conditions lead to less rapid price adjustment and therefore to distortions in relative prices that last longer?

To answer the first question, we investigate how the persistence of each price component is linked to its own volatility. As we explain below, if the persistence of shocks was the main driver of the observed persistence in price components, then we would expect to see a positive relation between own persistence and volatility for each price component. On the other hand, the absence of a positive estimated link would be evidence that price components have different adjustment rates because prices react differently to the shocks and not merely due to differences in the persistence of the shocks themselves. To answer the second question, we investigate how the persistence of each price component is linked to the volatility of other components. If volatility of, for instance, local conditions was detrimental to the adjustment to global conditions, then one would expect the persistence of the price response to global shocks to increase with the volatility of local shocks.

More precisely, letting $\rho_{il}(m_i)$, $\rho_{il}(m_l)$ and $\rho_{il}(m_{il})$ denote the (estimated) persistence parameters associated with, respectively, the good-specific, location-specific and idiosyncratic good-location specific components for each good and location pair in our sample²⁴, and letting $\sigma(m_{it}|i)$, $\sigma(m_{lt}|l)$

²⁴We recall that these persistence parameters are given by the sum of the coefficients characterizing the dynamics

and $\sigma(m_{ilt}|il)$ denote the (estimated) standard deviation over time of the good-specific (global micro), location-specific (local macro) and idiosyncratic good-location specific (local micro) components respectively, we estimate cross-sectional regressions of the following kind

$$\log \rho_{il}(m_*) = \mu + \theta_1 \log \sigma(m_{it}|i) + \theta_2 \log \sigma(m_{lt}|l) + \theta_3 \log \sigma(m_{ilt}|il) + \xi X_i + \zeta Z_l + u_{il} \quad (5)$$

where $*$ is either i , l or il , X_i is a set of good-specific controls, and Z_l a set of location-specific controls. Results are provided in the three different panels of Table 7. In the first panel, we explain the persistence associated with local macro shocks, in the second panel we explain the persistence associated with global micro shocks, and in the last panel we consider persistence associated with local micro shocks.

Standard time series properties tell us that the volatility of a component in prices, $\sigma(m_{*t}|*)$, is positively related to the persistence of the shocks underlying this component and to the volatility of the innovations driving these shocks, $\sigma(\epsilon_{*t}|*)$. Thus, if the persistence of a price component, $\rho_{il}(m_*)$, was merely linked to the persistence of the shock driving that component, the estimated relationship between the persistence and volatility of each price component would be positive. Conversely, there is no *a priori* reason why the volatility of the innovations, $\sigma(\epsilon_{*t}|*)$, driving each price component should be negatively related to the persistence of the shock.

Column (1) of Table 7 reports estimates of the bivariate relationship between price persistence in response to a shock and volatility associated with that same type of shock. The link is clearly negative for the local macro and micro components and insignificant for the global micro one. These findings underline the negative effect of the volatility of innovations on price persistence. This conclusion holds even for the global micro component. The finding of a zero coefficient in the latter case implies that the natural positive link between persistence of the global-micro shocks and price persistence, is wiped off by a negative impact of the volatility of global-micro innovations on price persistence. All in all, prices adjust more rapidly to components that have more volatile innovations.

In column (2) of Table 7, we explain persistence associated with each type of shock with volatility associated with other types of shocks in addition to own volatility. Looking at the first panel of the table for the case of local macro shocks, we see that the negative estimated link between price persistence and own volatility is preserved when one controls for the volatility of other components in prices: more volatile macro shocks increase the speed of price adjustment in response to these local macro shocks. At the same time, higher volatility in the global micro or local micro components decreases the speed of adjustment of prices in response to local macro shocks, as witnessed by the

of each component, i.e. $\rho_{il}(1; m_*)$ with $*$ being either i , l or il , using the notation introduced in equation (1).

positive estimated coefficients in the first and third row of the Table. Consistent with the imperfect information approach of price setting, more volatility in micro conditions leads to fuzzier perception and thus slower adjustment of prices to changes in macro conditions. Turning to the second panel of the table for the case of global micro shocks, an increase in own volatility is still found to have a negative but insignificant impact on the price persistence associated with the response to global micro shocks. Moreover, higher volatility in the local macro or the local micro components increases the price persistence associated with the response to global micro shocks. That is, more volatility of local conditions is associated with slower adjustment of prices to global conditions, again consistent with imperfect information models of price setting. All in all, more volatile micro conditions lead to more persistent relative price distortions due to slower response of prices to macro shocks, and more volatile local conditions lead to more persistent relative price distortions due to slower response of prices to global shocks.

It is remarkable that the effect of a marginal increase in the volatility of the local (macro or micro) components on the persistence of the global micro component shown in the second panel of Table 7 is at least twice as large as the effect of a marginal increase in the volatility of the micro (global or local) components on the persistence of the local macro component shown in the first panel of Table 7. Increasing local volatility is quantitatively more detrimental to the speed of adjustment of prices to global shocks, than increasing micro volatility is to the speed of adjustment of prices to macro shocks.

Results are somewhat different in the case of idiosyncratic shocks estimates for which are reported in the last panel of Table 7. As we can see in column (2) of Table 7, own volatility has no significant impact on own persistence in this case. As previously explained, the finding of a non-significant link implies that the speed of reaction to idiosyncratic components increases with the volatility of their innovations, so that the conclusions from column (1) are not overturned. Moreover, volatility associated with global shocks does not impact on the speed of adjustment of idiosyncratic shocks. Finally, more volatility in the local macro component leads to faster adjustment of prices in response to idiosyncratic shocks. All in all, volatility has either no detrimental effect on the reaction of prices to local micro shocks, or even speeds this up in the case of local macro volatility.

In column (3) of Table 7, we consider additional explanatory variables that control for certain country and goods characteristics, such as real GDP per capita and the share of world population for each country to capture income and scale effects respectively, as well as the average price of each good across locations to capture one aspect of good-specific tradeability. The results of column (2) are not qualitatively affected by these controls.

Our results suggest that distinguishing between global and local components is important in char-

acterizing the link between persistence and volatility, and, more broadly speaking, useful in discriminating between different models of price setting. According to these results, price setting models should be able to rationalize differences between the price response to global versus local shocks that are more pronounced than between macro and micro shocks. Explaining such differences in the rate of price adjustment to different types of shocks, could be achieved by resorting to models of endogenous imperfect perception of shocks, in the spirit of the recent contributions of Reis (2006), Maćkowiak and Wiederholt (2009), Woodford (2009) or Alvarez et al. (2010), where the relative cost of observing global conditions would be greater than the one associated with monitoring local ones, in the same manner (but more strikingly so) in which the relative cost of observing macro conditions is normally assumed to be greater than the one associated with monitoring micro ones. Another possibility would be to rely on labor market segmentation arguments, in the spirit of Carvalho and Lee (2010), with segmentation being greater between countries than within them in the same manner (but more strikingly so) that labor segmentation is greater across sectors than within sectors.

Furthermore, economic theory would need to come to grips with the positive link between local volatility and slowness of price adjustment to global shocks on the one hand, and between micro volatility and slowness of price adjustment to macro shocks on the other hand.²⁵ One possibility would be the rational inattention approach of Maćkowiak and Wiederholt (2009). When information capacity is fixed, an increase in the volatility of local (micro) components requires more attention devoted to the monitoring of local (micro) shocks which therefore hinders the monitoring of global (macro) ones. Thus, prices react more slowly to global (macro) shocks.²⁶ If one resorts to this approach, then one would also have to explain why the loss of processing capacities due to volatility in local conditions is more detrimental to the monitoring of global conditions than the loss of processing capacities due to volatility in micro conditions is to the monitoring of macro conditions.

²⁵Maćkowiak et al. (2009) discuss how the empirical link they find between the volatility of micro and macro components in price dynamics and the persistence of the price reaction to macro shocks is evidence against simple Calvo models and the sticky information model of Mankiw and Reis (2002).

²⁶This approach could also explain the additional interesting findings from Table 7 that pertain to the role of idiosyncratic local micro volatility and non-idiosyncratic price persistence. First, agents appear to allocate sufficient attention to idiosyncratic conditions, so that they have a good perception of it, no matter their volatility and the volatility of other components. However, an increase in the volatility of the idiosyncratic shock requires more attention capacity and therefore decreases the attention that can be allocated to the monitoring of non-idiosyncratic conditions. This explains why the persistence of both the global micro and local macro price components increases with the volatility of the idiosyncratic component. Second, for a given level of attention capacity allocated to monitoring non-idiosyncratic conditions, agents have to strike a balance between surveying global micro and local macro conditions. An increase in the volatility of local macro conditions raises the attention allocated to them but reduces the attention paid to global micro conditions. This would explain why an increase in the volatility of the local macro shock decreases the persistence of its own component in prices but raises the persistence of the global micro component. Likewise, an increase in the volatility of global micro conditions reduces the attention devoted to local macro conditions.

Finally, we note that sorting out local micro shocks from either global micro or local macro ones, reveals potential subtleties in the interaction between the volatility of shocks and the speed of adjustment of prices to shocks. In particular, the evidence that an increase in the volatility of local macro shocks decreases the persistence of the reaction to local micro shocks, while an increase in the variance of global micro shocks has no effect on the persistence of the reaction to local micro shocks, could signal that strategic complementarities in price-setting decisions are much more at stake across sectors within a country than for a given sector across countries.²⁷ This could be rationalized by resorting to the fact that market segmentation is more significant between countries than between sectors.

6 Conclusion

We have used a unique global microeconomic dataset of semiannual prices observed over two decades ending in March 2010, to consider how fast prices and relative prices respond to different types of shocks. Previous work has emphasized the difference between the reaction of prices to macro and micro shocks. We have shown that macro shocks are not all alike and that different types of micro shocks do not necessarily resemble each other either. More precisely, we have emphasized the distinction between global and local shocks, and found that for both macro and micro shocks alike, global components are associated with much more price persistence than local ones. The difference is much more striking when decomposing between global and local shocks rather than merely considering macro versus micro shocks. Moreover, we have shown that the price response to some types of micro shocks is slower than for some types of macro shocks. More specifically, global micro shocks are associated with a slower speed of price adjustment than local macro shocks. The latter are associated with relatively fast price adjustment as is the case for local micro shocks.

We also considered the relation between persistence of price adjustment and volatility for each type of shock. Our estimates imply that price adjustment to different types of changing conditions does not stem from the mere persistence of the shock driving the evolution of these conditions. Moreover, we found that more volatility in micro conditions is associated with slower adjustment of prices to macro shocks, and that more volatility in local conditions is associated with slower price adjustment to global shocks. In the latter case, the persistence-volatility link is at least twice as large as that in the micro-macro case.

²⁷The evidence that more variance in macro shocks increases the speed with which prices adjust is also reminiscent of the micro price studies showing that the frequency of price adjustment increases with the level of inflation, a result that is consistent with menu costs models of price setting. See e.g. Gagnon (2009) for Mexico and Alvarez et al. (2010) for Argentina.

Our findings support price-setting models that can explain differences in the speed of adjustment of prices in response to global versus local shocks, and differences in the link between persistence and volatility for global versus local components. Rational inattention models would be one natural candidate in that respect. The global-local distinction of macro and micro shocks provides a new more precise tool for assessing price setting models, as compared to a mere macro-micro breakdown. Models of price setting should be able to explain the ranking of the different types of shocks in terms of how fast prices respond to these shocks, with local micro shocks typically associated with somewhat faster adjustment than local macro ones which are in turn associated with much faster adjustment than global micro shocks.

Our work provides new facts that point towards the need of developing price-setting models with a spatial dimension. In particular, calibration exercises aiming at assessing the effectiveness of stabilization policies and the welfare cost of inflation would benefit from incorporating global shocks in their analysis. In such a context, geography could matter due to relative loss of information processing capacity or because of a higher degree of labor market segmentation across as compared to within locations. By considering only a single type of micro or macro shock, previous empirical work hides important heterogeneity in their effects, potentially giving rise to misleading inferences about the relative persistence of local macro shocks, typically monetary shocks, in micro prices. Given our findings, price setting theory models should not incorporate as much price rigidity in response to local macro shocks as previously thought based on existing empirical work. Overall, our work is suggestive of price-setting models consistent with fast price adjustment in response to local shocks and persistent price effects of international shocks. Dynamic price-setting models have typically been constructed in a closed economy setting. This can be understood in as far as, until now, there had not been as much evidence for prices responding differently to international as compared to local shocks. Our paper provides evidence that this is actually the case, pointing to the need for open macroeconomy dynamic price-setting models that can rationalize differences in the speed of adjustment of prices in response to different types of international and local shocks.

A Data

The discussion below has benefitted greatly from systematic direct communication with the EIU office over the past few years, and in particular, from the insights and detailed explanations offered to us by Jon Copestake, Editor of the Worldwide Cost of Living Surveys.

Selection of stores and goods

Considerable care is taken by the EIU team to assess accurately the normal or average prices international executives and their families can expect to encounter in the cities surveyed. Survey prices are gathered from three types of stores: supermarkets, medium-priced retailers and more expensive specialty shops. Only outlets where items of internationally comparable quality are available for normal sale are visited. While the majority of cities provide a wide selection of goods and stores at different price levels, this range narrows considerably at several locations. In some cities the entire range of prices has to be collected at the few stores where goods of internationally comparable quality are found. Local markets and bazaars are visited only if the goods available are of standard quality and if shopping in these areas does not present any danger.

For certain items like monthly rent and clothing, there are many subjective factors, questions of personal preferences and taste at play, as well as a wide variety of choice. Therefore, price data given for certain items should be considered to be merely an indication of the general level of prices in these categories. In general, the degree of comparability across locations is high but varies with the general availability of goods in a given city. Given that the survey takes place in 140 cities worldwide, it is not always the case that an identical product is taken in all cities for all items. For example, it is more likely that while London has a quality Burberry raincoat available, Brussels does not have the same item or brand and the correspondent has taken a price based on the designer raincoats that are available. For such products, prices will reflect the general availability and local demand conditions in a location. Given these concerns, one would want to consider subsamples that exclude products likely to be less homogeneous across locations. The latter category includes pretty much all clothing items, automobiles, and a number of other products. As a result, we felt the need to create a sub-sample of goods that are more likely to be comparable across locations. This restricted sample of homogeneous goods excludes more than one third of our complete sample of goods and services, such as “Women’s raincoat Burberry type”, “personal computer”, “family car”, and “Furnished residential apartment: 1 bedroom, moderate”. However, convergence rates obtained (not reported in the Tables) based on this more highly comparable sub-sample of goods are very similar to what we obtain when using the full sample of goods and services.

The price range presented in the survey utilized in the current study is for supermarkets or chains, and for mid-priced outlets. The EIU takes one representative price per store, sampling only one price from each of two type of stores, and generally surveys two stores per item for most products. As shown in Table 1, we use 100 distinct products that are reported at both a supermarket (or

chain) and a mid-priced store and an additional 76 distinct products and services that are only sampled once, for a total of 276 price observations in each location and year.

In all cases, the EIU aims to keep the same stores and the same brands and sizes in obtaining the price for each item, so as to ensure ongoing consistency between surveys in each location. Store and product consistency has been an aim of the survey since its inception. The aim of sampling the same stores has remained consistent and the ability to do so has varied based on specific events in certain years relating to availability or specific situations affecting correspondents, like being refused entry to a store under new management. However, such consistency depends on and varies within individual markets. The surveyors seek to keep to the same stores, brands and weights between surveys. However, given that the survey takes place simultaneously in 140 cities over a period of twenty years, there may be substitutions or changes. This can occur in an evolutionary sense as certain brands or stores or sizes overtake others as the popular interpretation of a particular item changes over time. Alternatively, there may be sudden changes in brand, store or item based on availability in the market during a particular period. For example, a store may close and a certain brand may become temporarily or permanently unavailable. In these cases, substitutes are sought to reflect the price of obtaining the item in question at that particular time. This is more common in less developed markets where availability and price can fluctuate on a day to day basis, but even mature markets are prone to pricing or availability shocks and other changes of this kind especially over longer periods. We note that while the BLS adapts its basket of goods regularly and also changes the weighting system based on consumption trends, the EIU seeks to be more generally representative and has for the most part not changed in this manner, in an attempt to ensure a consistent dataset of like for like products going back over time.

The general conclusion from the discussion in this sub-section is that the EIU city-level prices are highly comparable across both space and time, and are thus suitable for the study of LOP deviations and their evolution over time. That is, one can use these prices to understand both the degree of market segmentation at any given point in time, and the process of market integration over time. The data appear less suitable for overall cost of living comparisons across locations since the goods sampled do not necessarily reflect local preferences as much as the shopping basket of executives and other multinational employees and their families.

Sampling, seasonality, and sales

The fieldwork for the Worldwide Cost of Living Surveys is carried out on location by the EIU researchers during the first week of March for the Spring edition and during the first week of September for the Autumn edition. These data was especially compiled for us, since the standard historical data in the “cityprices” EIU publication is only available at the annual frequency. Since the data overwrites old data each year, the standard data typically made available historically by the EIU is September data. There are two types of exception to this. First, are cities surveyed annually and only in March. These are: Baku, Bratislava, Calgary, Douala, Harare, Port Moresby,

San Juan, and Tunis. For these cities, data is gathered since 2001 during the first week of March. Second, are cities where there are problems or delays in gathering data. These are individual cases and are not tracked, but it would generally be the case that such data is still gathered within a month or two, so that prices can still be relevant and comparable to other cities. Moreover, no such lags are allowed in high inflation locations.

The March and September dates for gathering data are specifically designed to avoid standard sales seasons, like traditional sales in December, January, May and June which take place in many countries. Correspondents are instructed not to take sale prices for items, but to take standard recommended retail prices. There is an element of common sense here as well though. That is, correspondents may take sales prices for general promotions if they feel the price reflects the “true worth” of an item. This might be the case for some items since retailers commonly use tactics of promoting an item by describing it as on “sale” when in fact they have previously artificially inflated the retail price of the item in order to later reduce it to a more reasonable price and make consumers think they are purchasing a bargain. This is true of items like CDs, wine, certain fresh food items, and other consumer goods. A few adjustments of the survey prices have been made in some cases where seasonal discount sales and changes in brand names, package sizes, and quality would have unduly distorted the index results. This procedure is limited to cases where it would not entail misrepresentation of actual prices in the EIU team’s judgement.

The conclusion from the above paragraph is that the astonishing price differences for specific items across cities observed by the EIU team, are not due to sales or discounting, as the EIU does not seek to include such seasonal data in the price survey.

Reliability of data

Given the above discussion, we have opted to be extremely conservative in removing entries that at first might appear to be price outliers. Moreover, we never opt to adjust prices for what might at first appear to be “obvious” mistakes, like misplacing a digit or otherwise using a wrong unit, or misplacing part of a price entry in previous or subsequent entries. In this respect, our treatment of the data is very different than Crucini and Shintani (2008).

We opted to treat the data as a rather reliable representation of actual prices since in our discussions with the EIU office it was convincingly explained to us that specifying for instance the price variance between surveys not to be less than half or more than twice the CPI rate would be an extremely narrow margin for highlighting outliers, as the EIU team has historically observed prices that regularly change by as much as four times or more the CPI rate, while other prices remain unchanged year after year or even move down. It was also explained to us, that every survey price is “sense checked” as it comes in compared to those returned six months ago and those returned one year ago. Sense checking is simply to ensure that prices look broadly comparable to those returned previously. However, the final prices reported in the EIU surveys are based on actual ones as returned from field correspondents in each city, and are never a calculation based on a ratio of expected price

movement to reported inflation levels. As a result, prices of individual items in the basket the EIU surveys can fluctuate wildly based on the basket snapshot that is taken.

For instance, a seemingly wrong but actually correct price entry comes from Casablanca in the case of bread. The figures for years 1992 to 1995 seem to be missing the initial digit “1”. This example of bread in Casablanca between 1992 and 1996 is a prime example of how EIU prices should be considered valid even if they look peculiar relative to general price trends. Between 1992 and 1995, Morocco suffered from a period of drought which caused three harvests to fail (1992, 1993, and 1995). This had an impact on economic growth and prompted a recession. In response, the government will have extended price controls on staples. In the Moroccan diet, bread is considered to be the staple food of the poor and would have been the first and most heavily price-regulated item. Upon recovery and under external pressure the government pledged to relax such controls in 1996. In the case of the survey, we can clearly see this reflected. Lower priced bread in line with the 1992-1995 prices may have been widely available before and after this period, but during this period shortages, economic stagnation, suppressed demand for more expensive consumer goods, and price controls may have meant that these were the only prices available for bread. This situation was rectified as Morocco emerged from this period. Similarly, many prices could be flagged in developing countries during times of instability as these experience massive fluctuations in prices dependent on localized supply and demand factors. Thus, the EIU suggests that users consider reasons why a particular price may deviate from expectation based on the political, social and economic market context, globally, nationally or at city level before removing a price entry.

Errors that emerge may be a currency issue where back-rates are recalculated to cater to currency redenominations caused by inflationary spikes, or where devalued/alternative exchange rates are in operation. It is possible that some prices might be entered in a sub-unit of currency (e.g. in pence or cents) then reported in standard units (e.g. in pounds, euros or dollars). However, this is something the EIU generally seeks to rectify on a rolling basis. Still, the EIU cannot double-check many of the prices since the citydata feed automatically takes from the source files. These are taken from surveys based on manually collected data by correspondents in each location. The price dataset is built as the accumulation of decades of data submitted from a variety of sources in a variety of formats. Any data collected before 1998, for example, would have been returned in paper format and manually input into the base files eventually used, and the original paper versions have long since been disposed of. Thus, the EIU may only be able to check sources for items after 1998 but such a process would be time-consuming and unnecessary according to the EIU office, since most of the price entries that appear at first to be errors are actually valid price entries.

Where a user has serious concerns, the EIU recommends removing a price rather than guessing at its original value. For instance, if we suspect that certain prices were simply misinput in error then this price would need to be removed from consideration as an outlier rather than tweaked into something resembling what it “should be”. While it is completely valid that a tiny proportion of the reported prices may include errors, the vast majority of prices are arguably valid snapshots at

the time of the survey and most prices that vary disproportionately with the CPI can be explained simply by looking at the context in which the prices were taken. Finally, even if all prices that move very differently than the CPI were assumed to be errors, these would represent a proportion below 0.5% of the available data points.

Nominal exchange rate issues

Spot exchange rates are applied to the city data surveyed by the EIU, and are available along with the price data for each year. The post rates are FT rates taken on the Friday of the first week of each month of the survey. For the standard Cityprices data typically made available by the EIU, data overwrites old data each year, thus most of the exchange rate data supplied historically is September data except in a few instances where a city is only surveyed every March in which case prices and exchange rates are from the first week of March. The exchange rate reported is the spot rate for the survey date when the data was gathered.

For pre-1999 price series, the conversion from legacy currencies to euros is made using the appropriate legacy currency, i.e. Ecu exchange rates prevailing at the time. Like Eurostat, the EIU has chosen to use the Ecu exchange rates because there is no universally agreed methodology for calculating a synthetic euro exchange rate. One Ecu was worth exactly one euro when the euro was launched at the beginning of 1999. The EIU used the September end-period rate from Eurostat to convert the legacy prices. Although surveys were completed for Euro cities at slightly different times in September, the EIU applied a standard rate to maintain relative prices between cities and also maintain distances between published Cost of Living indices.

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Table 1: Description of sample: list and classification of goods and locations

List of Countries		
Less Developed Countries	More Developed Countries	
Bangladesh	Argentina	Singapore
Brazil	Australia	Spain
China	Austria	Sweden
Colombia	Bahrain	Switzerland
Ecuador	Belgium	Taiwan
Egypt	Canada	UK
Guatemala	Czech Republic	US
India	Chile	
Indonesia	Denmark	
Iran	Finland	
Kenya	France	
Mexico	Germany	
Nigeria	Greece	
Pakistan	Hong Kong	
Panama	Hungary	
Paraguay	Israel	
Peru	Italy	
Philippines	Japan	
Poland	Korea	
Russia	Luxembourg	
Serbia	Malaysia	
South Africa	Netherlands	
Thailand	New Zealand	
Turkey	Norway	
Uruguay	Portugal	
Venezuela	Saudi Arabia	

Notes: Less developed countries have PPP-adjusted income per capita below the world mean (\$12000) for 1990–2007.

Table 1: Description of sample: list and classification of goods and locations

List of Cities			
In Less Developed Countries	In More Developed Countries		
ASUNCION	ADELAIDE	LOS ANGELES	TOKYO
BANGKOK	AL KHOBAR	LUXEMBOURG	TORONTO
BELJING	AMSTERDAM	LYON	VANCOUVER
BELGRADE	ATHENS	MADRID	VIENNA
BOGOTA	ATLANTA	MELBOURNE	WASHINGTON DC
CAIRO	AUCKLAND	MIAMI	WELLINGTON
CARACAS	BAHRAIN	MILAN	ZURICH
DHAKA	BARCELONA	MONTREAL	
GUATEMALA CITY	BERLIN	MUNICH	
ISTANBUL	BOSTON	NEW YORK	
JAKARTA	BRISBANE	OSAKA / KOBE	
JOHANNESBURG	BRUSSELS	OSLO	
KARACHI	BUDAPEST	PARIS	
LAGOS	BUENOS AIRES	PERTH	
LIMA	CHICAGO	PITTSBURGH	
MANILA	CLEVELAND	PRAGUE	
MEXICO CITY	COPENHAGEN	RIYADH	
MONTEVIDEO	FRANKFURT	ROME	
MOSCOW	GENEVA	SAN FRANCISCO	
NAIROBI	HAMBURG	SANTIAGO	
NEW DELHI	HELSINKI	SEATTLE	
PANAMA CITY	HONG KONG	SEOUL	
QUITO	HOUSTON	SINGAPORE	
RIO DE JANEIRO	JEDDAH	STOCKHOLM	
SAO PAULO	KUALA LUMPUR	SYDNEY	
TEHRAN	LISBON	TAIPEI	
WARSAW	LONDON	TEL AVIV	

Notes: Less developed countries have PPP-adjusted income per capita below the world mean (\$12000) for 1990–2007.

Table 1: Description of sample: list and classification of goods and locations

List of goods: Non traded

Annual premium for car insurance (high)	Laundry (one shirt) (mid-priced outlet)
Annual premium for car insurance (low)	Laundry (one shirt) (standard high-street outlet)
Babysitter's rate per hour (average)	Maid's monthly wages (full time) (average)
Business trip, typical daily cost	Man's haircut (tips included) (average)
Cost of a tune up (but no major repairs) (high)	Moderate hotel, single room, one night including breakfast (average)
Cost of a tune up (but no major repairs) (low)	One drink at bar of first class hotel (average)
Cost of developing 36 colour pictures (average)	One good seat at cinema (average)
Daily local newspaper (average)	Simple meal for one person (average)
Dry cleaning, man's suit (mid-priced outlet)	Taxi rate per additional kilometre (average)
Dry cleaning, man's suit (standard high-street outlet)	Taxi: airport to city centre (average)
Dry cleaning, trousers (mid-priced outlet)	Taxi: initial meter charge (average)
Dry cleaning, trousers (standard high-street outlet)	Three-course dinner at top restaurant for four people (average)
Dry cleaning, woman's dress (mid-priced outlet)	Telephone line, monthly rental (average)
Dry cleaning, woman's dress (standard high-street outlet)	Telephone, charge per local call from home (3 mins) (average)
Electricity, monthly bill for family of four (average)	Two-course meal for two people (average)
Fast food snack: hamburger, fries and drink (average)	Unfurnished residential apartment: 2 bedrooms (high)
Four best seats at cinema (average)	Unfurnished residential apartment: 2 bedrooms (moderate)
Four best seats at theatre or concert (average)	Unfurnished residential apartment: 3 bedrooms (high)
Furnished residential apartment: 1 bedroom (high)	Unfurnished residential apartment: 3 bedrooms (moderate)
Furnished residential apartment: 1 bedroom (moderate)	Unfurnished residential apartment: 4 bedrooms (high)
Furnished residential apartment: 2 bedrooms (high)	Unfurnished residential apartment: 4 bedrooms (moderate)
Furnished residential apartment: 2 bedrooms (moderate)	Unfurnished residential house: 3 bedrooms (high)
Furnished residential house: 3 bedrooms (high)	Unfurnished residential house: 3 bedrooms (moderate)
Furnished residential house: 3 bedrooms (moderate)	Unfurnished residential house: 4 bedrooms (high)
Hilton-type hotel, single room, one night including breakfast (average)	Unfurnished residential house: 4 bedrooms (moderate)
Hire car, weekly rate for lowest price classification (average)	Water, monthly bill for family of four (average)
Hire car, weekly rate for moderate price classification (average)	Woman's cut & blow dry (tips included) (average)
Hourly rate for domestic cleaning help (average)	Yearly road tax or registration fee (high)
Gas, monthly bill for family of four (average)	Yearly road tax or registration fee (low)

Table 1: Description of sample: list and classification of goods and locations

List of goods: Traded

Available at both a supermarket and a mid-priced store		
Apples (1 kg)	Flour, white (1 kg)	Peas, canned (250 g)
Aspirins (100 tablets)	Fresh fish (1 kg)	Pork: chops (1 kg)
Bacon (1 kg)	Frozen fish fingers (1 kg)	Pork: loin (1 kg)
Bananas (1 kg)	Frying pan (Teflon or good equivalent)	Potatoes (2 kg)
Batteries (two, size D/LR20)	Gin, Gilbey's or equivalent (700 ml)	Razor blades (five pieces)
Beef: filet mignon (1 kg)	Ground coffee (500 g)	Scotch whisky, six years old (700 ml)
Beef: ground or minced (1 kg)	Ham: whole (1 kg)	Shampoo & conditioner in one (400 ml)
Beef: roast (1 kg)	Hand lotion (125 ml)	Sliced pineapples, canned (500 g)
Beef: steak, entrecote (1 kg)	Insect-killer spray (330 g)	Soap (100 g)
Beef: stewing, shoulder (1 kg)	Instant coffee (125 g)	Spaghetti (1 kg)
Beer, local brand (1 l)	Lamb: chops (1 kg)	Sugar, white (1 kg)
Beer, top quality (330 ml)	Lamb: leg (1 kg)	Tea bags (25 bags)
Butter (500 g)	Lamb: Stewing (1 kg)	Toilet tissue (two rolls)
Carrots (1 kg)	Laundry detergent (3 l)	Tomatoes (1 kg)
Cheese, imported (500 g)	Lemons (1 kg)	Tomatoes, canned (250 g)
Chicken: fresh (1 kg)	Lettuce (one)	Tonic water (200 ml)
Chicken: frozen (1 kg)	Light bulbs (two, 60 watts)	Toothpaste with fluoride (120 g)
Cigarettes, local brand (pack of 20)	Liqueur, Cointreau (700 ml)	Veal: chops (1 kg)
Cigarettes, Marlboro (pack of 20)	Margarine (500g)	Veal: fillet (1 kg)
Coca-Cola (1 l)	Milk, pasteurised (1 l)	Veal: roast (1 kg)
Cocoa (250 g)	Mineral water (1 l)	Vermouth, Martini & Rossi (1 l)
Cognac, French VSOP (700 ml)	Mushrooms (1 kg)	White bread (1 kg)
Cornflakes (375 g)	Olive oil (1 l)	White rice (1 kg)
Dishwashing liquid (750 ml)	Onions (1 kg)	Wine, common table (750 ml)
Drinking chocolate (500 g)	Orange juice (1 l)	Wine, fine quality (750 ml)
Eggs (12)	Oranges (1 kg)	Wine, superior quality (750 ml)
Electric toaster (for two slices)	Peaches, canned (500 g)	Yoghurt, natural (150 g)
Facial tissues (box of 100)	Peanut or corn oil (1 l)	

Table 1: Description of sample: list and classification of goods and locations

List of goods: Traded (continued)	
Available at both a chain and mid-priced/branded stores	Available only once
Boy's dress trousers	Compact car (1300-1799 cc) (high)
Boy's jacket, smart	Compact car (1300-1799 cc) (low)
Child's shoes, sportswear	Compact disc album (average)
Child's shoes, dresswear	Deluxe car (2500 cc upwards) (high)
Child's jeans	Deluxe car (2500 cc upwards) (low)
Girl's dress	Family car (1800-2499 cc) (high)
Lipstick (deluxe type)	Family car (1800-2499 cc) (high)
Men's business shirt, white	Family car (1800-2499 cc) (low)
Men's business suit, two piece, medium weight	Heating oil (100 l) (average)
Men's raincoat, Burberry type	International foreign daily newspaper (average)
Men's shoes, business wear	International weekly news magazine (Time) (average)
Socks, wool mixture	Kodak colour film (36 exposures) (average)
Women's cardigan sweater	Low priced car (900-1299 cc) (high)
Women's dress, ready to wear, daytime	Low priced car (900-1299 cc) (low)
Women's raincoat, Burberry type	Paperback novel (at bookstore) (average)
Women's shoes, town	Paperback novel (at bookstore) (average)
Women's tights, panty hose	Pipe tobacco (50 g) (average)
	Regular unleaded petrol (1 l) (average)
	Television, colour (66 cm) (average)

Table 2: Cross-section distribution of price level, volatility and persistence

CITY LEVEL ANALYSIS					
CURRENCY UNIT: USD					
SAMPLE PERIOD: 1990–2010					
	WHS	LDC	DEV	NT	TR
LOG-PRICE, p_{ilt}					
Mean	2.49	2.18	2.60	4.26	2.03
Median	1.89	1.52	2.02	4.42	1.52
95 th	7.58	7.40	7.64	7.97	6.29
5 th	-.56	-.84	-.40	.08	-.61
Std-Dev.	2.57	2.60	2.55	2.65	2.34
TIME VOLATILITY, $\sigma(p_{ilt} il)$					
Mean	.33	.41	.30	.34	.32
Median	.28	.36	.25	.28	.27
95 th	.62	.77	.52	.67	.61
5 th	.14	.17	.13	.13	.14
Std-Dev.	.26	.29	.23	.32	.24
AUTO-CORRELATION, $\rho(p_{ilt}, p_{ilt-1} il)$					
Mean	.81	.77	.82	.85	.80
Median	.84	.81	.86	.88	.83
95 th	.99	.97	1.00	1.01	.99
5 th	.49	.44	.51	.56	.47
Std-Dev.	.16	.17	.16	.15	.17
# of obs	831193	218694	612499	170150	661043

Notes: WHS = Whole set of goods and locations; LDC = locations in less developed countries (PPP-adjusted income per capita < \$12000); DEV = locations in more developed countries; NT = non-traded goods; TR = traded goods

Table 3: Unit-root tests

CITY LEVEL ANALYSIS			
CURRENCY UNIT: USD			
SAMPLE PERIOD: 1990–2010			
	WHS	DEV	NT
PRICE LEVELS, \bar{p}_t (global mean)			
t-stat, t	-0.07		
Significance level, $s(t)$.95		
DEVIATIONS FROM THE LOP, \bar{q}_{it} (city mean)			
Average t-stat, $\bar{t} = \frac{1}{n_l} \sum_l t_l$	-1.56	-1.59	
Significance level, $s(\bar{t})$.059	.056	
# of cities with $s(t_l) < .10$	62 out of 88	44 out of 61	
GOODS RELATIVE PRICES, \bar{r}_{it} (goods mean)			
Average t-stat, $\bar{t} = \frac{1}{n_i} \sum_i t_i$	-1.73		-1.66
Significance level, $s(\bar{t})$.042		.048
# of goods with $s(t_i) < .10$	183 out of 276		39 out of 57
DEVIATIONS FROM THE LOP, q_{ilt}			
Average t-stat, $\bar{t} = \frac{1}{n_l} \sum_l t_l$	-1.84	-1.85	
Significance level, $s(\bar{t})$.034	.032	
# of cities with $s(t_l) < .10$	85 out of 88	59 out of 61	
GOODS RELATIVE PRICES, r_{ilt}			
Average t-stat, $\bar{t} = \frac{1}{n_i} \sum_i t_i$	-2.14		-2.01
Significance level, $s(\bar{t})$.016		.022
# of goods with $s(t_i) < .10$	271 out of 276		56 out of 57
# of locations	88	61	88
# of goods	276	276	57

Notes: ADF (for \bar{p}_t) and Pesaran (2007) CADF (otherwise) unit-root tests with 3 lags. WHS = Whole set of goods and locations; DEV = locations in more developed countries (PPP-adjusted income per capita > \$12000); NT = non-traded goods.

Table 4: Persistence estimates

COUNTRY LEVEL ANALYSIS					
CURRENCY UNIT: USD					
SAMPLE PERIOD: 1990–2010					
	WHS	LDC	DEV	NT	TR
RESPONSE TO					
<i>Local Macro shocks</i>					
ρ (mean)	.67	.61	.72	.68	.66
std-dev (cross-section)	.73	.75	.71	.69	.74
95% confidence interval	[.66 .68]	[.59 .63]	[.70 .74]	[.65 .71]	[.65 .67]
half-life	10.38	8.41	12.66	10.78	10.01
<i>Global Micro shocks</i>					
ρ (mean)	.79	.83	.76	.81	.78
std-dev (cross-section)	1.50	1.77	1.19	1.66	1.45
95% confidence interval	[.76 .82]	[.78 .88]	[.73 .79]	[.74 .88]	[.75 .81]
half-life	17.64	22.32	15.15	19.74	16.74
<i>Local Micro shocks</i>					
ρ (mean)	.55	.51	.58	.68	.51
std-dev (cross-section)	.65	.43	.81	.70	.63
95% confidence interval	[.54 .56]	[.50 .52]	[.56 .60]	[.65 .71]	[.50 .52]
half-life	6.96	6.17	7.63	10.78	6.18
<i>Macro shocks</i>					
ρ (mean)	.82	.81	.82	.80	.82
std-dev (cross-section)	.56	.53	.59	.71	.52
95% confidence interval	[.81 .83]	[.80 .82]	[.81 .83]	[.77 .83]	[.81 .83]
half-life	20.96	19.74	20.96	18.63	20.96
<i>Micro shocks</i>					
ρ (mean)	.73	.71	.75	.79	.71
std-dev (cross-section)	.34	.34	.33	.34	.33
95% confidence interval	[.72 .74]	[.70 .72]	[.74 .76]	[.78 .80]	[.70 .72]
half-life	13.21	12.14	14.46	17.64	12.14
# of locations	49	26	23	49	49
# of goods	276	276	276	58	218

Notes: Persistence parameter estimates applying Pesaran (2006) mean-group procedure (CCEMG) to equations (3) and (4) with 3 lags. Sample of countries excluding euro-area members other than Germany. WHS = Whole set of goods and locations; LDC = locations in less developed countries (PPP-adjusted income per capita < \$12000); DEV = locations in more developed countries; NT = non-traded goods; TR = traded goods. Confidence bands are calculated using the MG estimator variance, $\sqrt{\Delta/n}$, where $\Delta = (1/n) \sum_{il} (\rho_{il} - \bar{\rho})^2$, with $n = \sum_i n_{li}$ the number of parameter estimates.

Table 5: Persistence estimates – Robustness checks

SAMPLE PERIOD: 1990–2010					
	(1)	(2)	(3)	(4)	(5)
Currency unit	USD	STG	JPY	USD	USD
RESPONSE TO					
<i>Local Macro shocks</i>					
ρ (mean)	.66	.63	.65	.66	.68
std-dev (cross-section)	.72	.55	.59	.68	.78
95% confidence interval	[.65 .67]	[.62 .64]	[.64 .66]	[.65 .67]	[.67 .69]
half-life	10.01	9.00	9.65	10.01	10.78
<i>Global Micro shocks</i>					
ρ (mean)	.81	.84	.85	.82	.78
std-dev (cross-section)	1.41	1.38	1.25	1.37	1.39
95% confidence interval	[.79 .83]	[.82 .86]	[.83 .87]	[.79 .85]	[.76 .80]
half-life	19.74	23.85	25.59	20.96	16.74
<i>Local Micro shocks</i>					
ρ (mean)	.56	.60	.62	.60	.54
std-dev (cross-section)	.68	.75	.64	.78	.61
95% confidence interval	[.55 .57]	[.59 .61]	[.61 .63]	[.58 .62]	[.53 .55]
half-life	7.17	8.14	8.70	8.14	6.75
# of locations	59	59	59	59	88
# of goods	276	276	276	176	276

Notes: Persistence estimates applying Pesaran (2006) mean-group procedure (CCEMG) to equations (3) and (4) with 3 lags. Complete sample of goods and countries, including euro-area members. **(1)** Prices converted in US Dollars; **(2)** Prices converted in Sterling pounds; **(3)** Prices converted in Japanese yen; **(4)** Average of mid-priced and supermarket (or chain) stores where available, for prices converted in US Dollars; **(5)** City level analysis, for prices converted in US Dollars. Confidence bands are calculated using the MG estimator variance, $\sqrt{\Delta/n}$, where $\Delta = (1/n) \sum_{il} (\rho_{il} - \bar{\rho})^2$, with $n = \sum_i n_{l|i}$ the number of individual parameter estimates.

Table 6: Time-variance of components (average)

COUNTRY LEVEL ANALYSIS					
CURRENCY UNIT: USD					
SAMPLE PERIOD: 1990–2010					
	WHS	LDC	DEV	NT	TR
TOTAL					
$E_{il} \{V(p_{ilt} il)\}$.18	.24	.17	.24	.18
GLOBAL MACRO					
$\widehat{V}(m_t)$.02	.02	.02	.02	.02
Share in $E_{il} \{V(p_{ilt} il)\}$	11	8	12	8	11
LOCAL MACRO					
$E_l \{\widehat{V}(m_{lt} l)\}$.03	.05	.02	.03	.03
Share in $E_{il} \{V(p_{ilt} il)\}$	17	21	12	12.5	17
GLOBAL MICRO					
$E_i \{\widehat{V}(m_{it} i)\}$.07	.07	.07	.10	.06
Share in $E_{il} \{V(p_{ilt} il)\}$	39	29	41	42	33
LOCAL MICRO					
$E_{il} \{\widehat{V}(m_{ilt} il)\}$.06	.10	.06	.09	.07
Share in $E_{il} \{V(p_{ilt} il)\}$	33	42	35	37.5	39

Notes: Average of time variances across goods and locations for a sample of countries excluding euro-area members other than Germany. WHS = Whole set of goods and locations; LDC = locations in less developed countries (PPP-adjusted income per capita < \$12000); DEV = locations in more developed countries; NT = non-traded goods; TR = traded goods.

Table 7: Cross-section determinants of persistence

	(1)	(2)	(3)
LOCAL MACRO, $\log \rho_{il}(m_l)$			
$\log \sigma(m_{it} i)$.04*** (.015)	.04*** (.015)
$\log \sigma(m_{it} l)$	-.06*** (.021)	-.09*** (.023)	-.13*** (.027)
$\log \sigma(m_{ilt} il)$.07** (.025)	.06** (.025)
(log) gdp per capita			-.01 (.016)
share of World pop			-1.60*** (.606)
good (log) price average			-.02*** (.004)
GLOBAL MICRO, $\log \rho_{il}(m_i)$			
$\log \sigma(m_{it} i)$	-.00 (.016)	-.01 (.016)	-.01 (.016)
$\log \sigma(m_{it} l)$.19*** (.026)	.09*** (.032)
$\log \sigma(m_{ilt} il)$.12*** (.026)	.11*** (.026)
(log) gdp per capita			-.10*** (.017)
share of World pop			-1.85*** (.509)
good (log) price average			.01* (.005)
LOCAL MICRO, $\log \rho_{il}(m_{il})$			
$\log \sigma(m_{it} i)$		-.00 (.013)	.00 (.013)
$\log \sigma(m_{it} l)$		-.16*** (.017)	-.14*** (.021)
$\log \sigma(m_{ilt} il)$	-.07*** (.017)	.02 (.017)	-.00 (.018)
(log) gdp per capita			.01 (.012)
share of World pop			.21 (.440)
good (log) price average			.03*** (.003)

Notes: OLS estimates of equation (5) for prices converted in USD observed over 1990-2010. Whole set of goods and locations excluding euro-area members other than Germany. Numbers in brackets are White-robust standards errors of estimates. ***, **, *, denote, respectively, significance at the 1%, 5% and 10% levels.