Prices and Global Inequality: New Evidence from Worldwide Scanner Data*

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Abstract

How do prices affect inequality and living standards worldwide? To address existing biases in the measurement of prices and expenditure patterns across countries, this paper introduces a new global scanner database. This dataset provides harmonized barcode-level data on expenditures and prices for fast-moving and slow-moving consumer goods during the last decade in thirty four countries, which include both developing (e.g., Brazil, China, India, and South Africa) and developed countries (e.g., the United States, Russia, and most European countries) and represent 70% of world GDP and 60% of world population. We first quantify the importance of several common biases stemming from substitution, product variety, and taste shocks, and we characterize how these biases vary with the level of economic development. We then build purchasing power parity indices using identical barcodes across countries. We find that adjustments for product variety, non-homotheticicities, and taste heterogeneity are quantitatively important. Our results suggest that standard price indices from the World Bank's International Comparison Program (ICP) are biased downward for low-income and more populated countries, implying that international inequality is underestimated and that standard estimates of worldwide GDP per capita are biased upward. Using our preferred CES PPP index accounting for product variety instead of standard ICP indices, we find that the Gini coefficient across countries increases by 40%, while worldwide GDP per capita falls by 22%. Overall, these findings indicate that using micro data on prices and expenditures is crucial to accurately describe patterns of inclusive growth worldwide.

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I Introduction

How do prices affect inequality and living standards worldwide? Despite extensive research, this question remains debated due to potential biases in existing measures of prices and expenditure patterns across countries. To address this issue, this paper introduces a new global scanner database, covering both fast-moving consumer goods (covering primarily nondurable goods including food, beverages, personal care, etc.) and slow-moving consumer goods (including durables such as consumer electronics, dryers, washers, etc.). This dataset provides harmonized barcode-level data on expenditures and prices in thirty four countries, including developing (e.g., Brazil, China, India, and South Africa) and developed countries (e.g., the United States, Russia, and most European countries) for the last decade.

We proceed in three steps. We first study inflation within country over times: we assess the importance of several biases that afflict standard price indices and measure inflation inequality within countries over time. Second, we conduct cross-country comparisons, matching tens of thousands of identical barcodes across countries. Third, we implement additional analyses to assess the external validity of our findings, outside the sample of fast-moving and slow-moving consumer goods covered by the global scanner data.

The analysis of inflation within countries over time yields three main results. First, we quantify the extent of substitution bias and entry-exit bias in all countries, and find that the entry-exit bias leads to a large upward bias in standard inflation measures in almost all countries. When correcting for this bias, we find that most countries have experienced deflation in the past decade. The entry-exit bias is particularly large for slow-moving consumer goods. Second, focusing on the fast-moving consumer goods data, we compute household-specific price indices and find that inflation inequality has been a worldwide phenomenon in the past ten years. In most countries, inflation has been lower and product variety has increased faster in product categories catering to higher-income households. Third, we study changes in global market concentration and market power over time. We estimate markups structurally using expenditure patterns and estimated demand elasticities. We find that global market power has remained stable over the past decade and did not constitute a significant source of inflation or inequality.

In the second part of the paper, we build purchasing power parity (PPP) indices using identical barcodes across countries. Three main findings stand out. First, we find that accounting for differences in product variety across countries, which standard PPP indices cannot do, is essential to accurately characterize cross-country differences in purchasing power. For example, Italy has a lower cost of living than Germany with standard indices without the adjustment for product variety, but a higher cost of living with the adjustment. Second, we also find that PPP indices between countries vary significantly depending on which household income serves as the reference level. For example, Italy is significantly more expensive than Germany for households at the top and bottom of the income distribution, but less so for households in the middle class. Rather than focusing on a single PPP index for each pair of countries, we derive micro-founded non-homothetic PPP indices, with an intuitive money-metric interpretation, that can be used to characterize differences in purchasing power along the household income distributions in all countries. Third, we compute price indices which allow for taste differences across countries, which standard PPP indices cannot do, and find that taste differences significantly affect PPP indices worldwide.

Next, we study whether the PPP biases are related to the level of economic development and assess how they affect international real income inequality, in the spirit of Almås (2012). We find that our PPP indices, using either FMCG or SMCG scanner data, imply considerably larger international inequality than the standard PPP index from the World Bank's International Comparison Program (ICP) program. Compared with standard PWT incomes (Feenstra et al. (2015)), we find that estimates of real incomes based on exchange rates (which implicitly assume that PPP holds) are closer to our estimates with PPP indices from scanner data. Our estimates indicate that standard PPP indices undersestimate the price level in low-income countries and overestimate it in high-income countries, thus underestimating international inequality and overestimating world GDP per capita. Using our preferred CES PPP index accounting for product variety instead of standard ICP indices, we find that the international Gini coefficient increases by 40% and worldwide GDP per capita falls by 22%.

In ongoing work, we assess the external validity of our findings beyond fast-moving and slow-moving consumer goods. We first take a structural approach, using shifts in relative Engel curves to infer changes in overall welfare from our data. We then check the external validity of some of our findings directly by using data on prices and expenditures from national statistical agencies, which cover the full consumption basket of consumers.

This paper complements and advances the existing literature on price and welfare measurement in three main ways. First, we present international evidence on biases in price measurement using a large panel dataset of fast-moving consumer goods data, while prior work has studied single countries in isolation, focusing on the United States (e.g., Aguiar and Hurst (2007), Broda and

Weinstein (2010), Kaplan and Schulhofer-Wohl (2017), Jaravel (2019), Argente and Lee (2020)). To date, there is no evidence of the biases in welfare measurement stemming from product variety, substitution effects or mismeasured quality changes in a large set of developing countries, which are covered in our dataset (including in particular China, India, and Brazil). In recent work, Feenstra et al. (2020) compare the cost of living for cities in China and in the United States using two sources of barcode data: scanner data from grocery stores, covering 4 product categories in 22 cities in China; and prices for grocery-store products scraped from a phone application. Second, we present for the first time evidence on biases in price measurement using slow-moving consumer goods data, which cover important categories of durable goods such as major domestic appliances where price mismeasurement could be large. In contrast, prior work on scanner data has restricted attention to nondurables by studing fast-moving consumer goods data. Third, we advance the literature on PPP measurement by (i) implementing a large-scale barcode-level match to identify tens of thousands of identical products in a large set of countries, and (ii) accounting for heterogeneity in PPP indices across households within countries. Only a handful of studies, including Deaton et al. (2004) and Almas and Sorensen (2020), have attempted to compute income-group-specific PPP indices, using survey data subject to potential quality biases across countries.[1]

The paper is organized as follows. Section 2 presents the data and summary statistics. Section 3 reports the results on biases affecting inflation measurement within countries over time. Section 4 present our new PPP estimates. Section 5 draws implications for the measurement of international inequality and worldwide GDP per capita. Section 6 presents the analysis of external validity. The Online Appendix presents the data in greater detail.

II Data

We briefly summarize the main features of the data, and highlight the key advantages of scanner data for welfare measurement.

II.A Data Construction and Summary Statistics

The analysis leverages two different types of scanner data. First, data from household panels are used. These household panels are run by internationally active research marketing companies and

[1] In recent work, Argente et al. (2019) use scanner data on fast-moving consumer goods for PPP comparisons in two countries, Mexico and the United States. They estimate PPP indices for a representative agent, using a demand system allowing non-homotheticities, but do not estimate heterogeneity across the household income distribution. As discussed in Section 4, their approach to non-homotheticities introduces a mechanical bias in the non-homothetic PPP estimate for the representative agent due to the curvature of the utility function.

largely constitute representative samples of the household population of the respective country. The information collected covers purchases of fast-moving consumer goods (FMCG) for thirty-five countries on all continents. In 2015, the population of these countries was 4.4 billion people, or 61.5% over the world population. Their PPP-adjusted GDP, according to the Penn World Table, accounted for 70.9% of world GDP in that year. The data stem from the two market research companies, GfK and Kantar, with the exception of the U.S., where the data is from IRI.[2]

For the purpose of our study, a major advantage of the international fast-moving consumer goods panel dataset is that it provides information not only about the quantity of products bought and the price paid but also the (socio-economic) characteristics of the buyers. Since the objective of household panels is to provide insights into the shopping behavior of the entirety of a country's households, their population is defined by the data provider as the set of all private households (with permanent residence) in that country. The panels are constructed to be representative of the populations of buyers in each country. The Online Appendix provides a more detailed discussion of the data construction steps.

With a few exceptions, the data span at least six years for each country, covering the time period 2013 to 2019. For several countries, data are available for over ten years (Austria, Belgium, Germany, Spain, France, Netherlands, Sweden, and the UK). The number of households included in the panel depends on the size of a country but is usually considerable. It ranges from about 1,000 for Bolivia to almost 130,000 for the U.S. The statistics for income and its distribution across panel members show that the panels in each country cover households widely spread across the income distribution.[3] Online Appendix Table A1 lists all countries and years for which we can compute year-on-year inflation using the fast-moving consumer goods dataset.

The second data source is data from the GfK Point Of Sale (POS) panel, which provides global coverage for about 60 countries. The POS panel is a regular, comprehensive survey to monitor sales of so-called slow-moving consumer goods (SMCG). Products from 23 sectors are recorded in the POS panel, which are divided into 78 categories.[4] The purchases recorded include both in-store and online purchases. The data generally span at least six years for each country, until (and including)

[2] The aim of these market research companies with such panels is to provide insights into the dynamics of sales of products and the purchasing behavior of households.

[3] The Online Appendix discusses the extent to which the household panels can be considered to be representative of the population of households in a given country. Although there are limitations in low-income countries, these constraints do not affect the main results of our analysis.

[4] These categories include automotive, baby care, bags and cases, consumer electronics, decorative products, furniture, gardening, hearing devices, houseware, information technology, light and building, major domestic appliances, office products, pet care, small domestic appliances, stationery, telecommunications products, and tools.

2020. For several countries, data are available for longer time periods. The main limitation of this data source is that socio-demographic characteristics of the buyers are not available, therefore we focus on the FMCG data for several parts of the analysis.

To characterize data coverage, Table 1 reports the goods subcategories underlying the computation of the consumer price index in the euro area for which sanner data is available. For illustrative purposes, the table also includes weights of the respective subcategories for Germany in the year 2020. The table shows that the coverage is broad for several (E)COICOP categories, including the food and beverage sectors, as well as for all sectors comprising electronic goods (understood in a broad sense) and goods purchased in DIY markets. The FMCG and SMCG datasets combined account for approximately 50% of household expenditures on goods and 25% of total household expenditures. The FMCG dataset alone accounts for approximatley 40% of expenditures on goods and 15% of total household expenditures.

Next, we briefly highlight the key advantages of scanner data for welfare measurement.

II.B Key Benefits of Global Scanner Data for Welfare Measurement

Global scanner can help address five important shortcomings in the existing literature on the measurement of economic development and economic growth.

First, it is very difficult to find comparable goods across countries to accurately measure price differences and hence differences in purchasing power (see, e.g., the International Comparison Program of the World Bank), but it is possible to do so by linking identical products using their barcodes. Second, it is challenging to properly account for the impact of the introduction of new products, or of changes in product variety, on purchasing power (e.g. Feenstra (1994), Broda and Weinstein (2006), Broda and Weinstein (2010)), but it possible to do so with scanner data by keeping track of the introduction and exit of products. Third, scanner data make it possible to observe prices effectively paid by households (rather than posted prices). Fourth, for fast-moving consumer goods, rich socio-demographic characteristics make it possible to study inflation heterogeneity across household types and locations within the same country.

III Quality-adjusted Inflation within Countries

In this the first part of the analysis, we focus on inflation within countries over time.

III.A The Gerschenkron effect over time

First, we quantify the extent of substitution bias in the price indices used to measure inflation over time in countries across the spectrum of economic development. Substitution bias, also called the "Gerschenkron effect", is the recognition that when intertemporal price and quantity relatives are negatively correlated an "early-weighted" aggregate will grow faster than a "late-weighted" aggregate (Gerschenkron (1947)). Although this bias has been largely documented in country studies, it is not known whether it varies systematically with the level of economic development. If it did, then comparison of growth rates between countries should be adjusted accordingly.

Results for fast-moving consumer goods. The results for substitution bias are reported in Figure 1, which presents price indices for the fifteen largest economies in our sample for fast-moving consumer goods. We compute several standard price indices on the set of goods (barcodes) that are available across consecutive years. Different price indices put different weights on product-level price changes, i.e. they handle substitution effects differently:

$$
\begin{aligned}
1+\pi_{t,t+1}^{Laspeyres} &\equiv \sum_i s_{i,t} \cdot \frac{p_{i,t+1}}{p_{i,t}} \\
1+\pi_{t,t+1}^{Paasche} &\equiv \left(1+\pi_{t+1,t}^{Laspeyres,h}\right)^{-1} \\
1+\pi_{t,t+1}^{Fisher} &\equiv \sqrt{\left(1+\pi_{t,t+1}^{Laspeyres}\right)\cdot\left(1+\pi_{t,t+1}^{Paasche}\right)} \\
1+\pi_{t,t+1}^{Tornqvist,h} &\equiv \Pi_i \left(\frac{p_{i,t+1}}{p_{i,t}}\right)^{\frac{s_{i,t}+s_{i,t+1}}{2}} \\
1+\pi_{t,t+1}^{CES} &\equiv \Pi_i \left(\frac{p_{i,t+1}}{p_{i,t}}\right)^{w_{i,t,t+1}}
\end{aligned}
$$

with $p_{i,t+1}$ price, $s_{i,t}$ spending share at t for each barcode i, and $w_{i,t,t+1}$ the "log-change ideal weights" of Sato (1976) and Vartia (1976).

As shown in Figure 1, the Laspeyres index (which is commonly used by most statistical agencies) significantly overstates inflation in all countries, while Paasche understates it. All superlative price indices (Fisher, Tornqvist and CES) are very close to each other. The difference between the Laspeyres index and the superlative indices reflects substitution bias. The results show that using up-to-date expenditure weights is important to accurately measure inflation, and that the magnitude of substitution bias is quite similar (as a fraction of average inflation) in all countries. Results for additional price indices are reported in Online Appendix Table A1, which reports the patterns for all countries for completeness and paints a similar picture overall.

Results for slow-moving consumer goods. Figure 2 report the results for slow-moving consumer goods. Slow-moving consumer goods available across consecutive years are characterized by large deflation in almost all countries, with the exception of Turkey. The rates of deflation are high in developing countries like China and India, at around -30% from 2017 to 2020, slightly more than the U.K., Germany, Spain, Italy, and France, where cumulative deflation was about 20% during the same period. As with fast-moving consumer goods, the magnitude of substitution bias is quite similar in all countries, as a fraction of average inflation.

III.B Product variety bias over time

Second, we estimate the impact of creative destruction — the entry and exit of goods — on inflation across countries. We find find that the entry-exit bias leads to a large upward bias in standard inflation measures in almost all countries. The results are reported in Figures 3 and 4. We account for the amount of consumer surplus that is created by entry and destroyed by exit using a CES price index. Following Feenstra (1994), the CES index with entry and exit of goods is:

$$\Omega^{CES} = \Pi^{CES} \cdot \left(\frac{1 + Growth\ Rate\ of\ Spending\ on\ Continued\ Products}{1 + Growth\ Rate\ of\ Total\ Spending} \right)^{\frac{1}{\sigma - 1}} \tag{1}$$

where Π^{CES} is the CES price index for continued goods. We study the sensitivity of the results of the choice of the elasticity of substitution σ, studying the relevant range from the literature (e..g, Broda and Weinstein (2010), DellaVigna and Gentzkow (2019)).

Results for fast-moving consumer goods. Figure 3 shows that the adjustment for product variety leads to a significant fall in effective inflation for fast-moving consumer goods. Because product variety is expanding in almost all countries over time, and because consumers have a taste for variety, conventional indices overstate the change in cost of living. With the adjustment for expanding productive variety, we find that most countries have experienced deflation in the past decade. Although biases from product variety was documented in prior work by Broda and Weinstein (2010), using scanner data in the United States, it was not know whether this bias was similar in other countries and whether it persisted in low-inflation, low-growth environments like in the 2010s.

Although most countries experience deflation after the adjustment for product variety, there are some important exceptions to this rule. In countries with higher inflation rates, notably Brazil, Argentina, Russia, and Turkey, the correction for product variety is not enough to offset the high inflation rates. In some cases, product variety even declines over time and strengthens inflation, for example in Russia and Turkey.

Results for slow-moving consumer goods. Figure 4 shows that the correction for product variety is even more important in the sample of slow-moving consumer goods. In China and India, cumulative inflation falls to about -50% once net entry is accounted for. Similarly large adjustments are observed in high-income countries including the U.K, Germany, France, Spain, and Italy. In Turkey, the correction for net entry is sufficiently large to induce deflation, even though inflation on continued good was positive. In most countries, the correction for net entry yields a fall in cumulative inflation of about 20 percentage points over three years. These results confirm that it is essential to account for product variety to accurately measure inflation, but that the magnitude of the bias does not appear to systematically vary with the level of economic development.

III.C Inflation inequality and household heterogeneity

Next, we compute inflation indices for different household groups.[5] Prior work has documented inflation inequality in the United States, i.e. the fact that lower income households experienced higher inflation (e.g., Jaravel (2019)), but it is not known whether this finding applies more broadly and whether it persists in the low-inflation environment of recent years.

Figures 5 and 6 report the results in our broad sample of countries. We repeat the computation of the CES price index, with and without the adjustment for with entry and exit of goods, separately for households in the top and bottom quintiles of the income distribution. Figure 5 reports these indices for each household group over time in each country. To facilitate the comparison between group, Figure 6 reports the cumulative inflation difference in percentage points over the course of the sample.

In most countries, we find that inflation has been lower and product variety has increased faster in product categories catering to higher-income households. In other words, inflation inequality has been a worldwide phenomenon in the past ten years. Inflation inequality results from differences in inflation rates on continued products (available across consecutive years) but also from the patterns of entry and exit. In some countries like China, most of inflation inequality results from differential entry and exit — higher income households benefit more from increased product variety. There are, however, a few important exceptions to inflation inequality. For example, we do not observe inflation inequality in Germany or in the U.K.

In ongoing work, we compute inflation at the household level in all countries. We find that there is significant household-level heterogeneity in inflation rates in all countries.

[5]Given the need for information on households' socoi-demographic characterisitics, we focus on fast-moving consumer goods in what follows.

III.D Global market power, markups and inflation

The scanner data are useful for this exercise because they allow for measurement of the degree of market concentration effectively faced by consumers, which to the best of our knowledge has not been examined in prior work. Most prior work has focus on studying market power in the United States and Europe from the point of view of firms and workers (e.g., De Loecker et al. (2020), Autor et al. (2017)). Instead, we analyse market concentration from the perspective of consumers and implement this analysis in a consistent way across a large number of countries worldwide.

We find that, in most countries, concentration ratios have been relatively flat over the past decade, for both retailers and manufacturers. These results suggest that global market power has remained stable over the past decade and did not constitute a significant source of inflation. The results are similar when we compute market concentration from the point of view of different consumer groups, for example by income groups and age groups. The fact that there were no systematic differences in concentration trends across household groups suggests that changes in global market power have not contributed to rising inequality.

These results stand in contrast with the rapidly expanding literature studying long-term trends in concentration from the point of view of producers. Our findings show that concentration trends from the perspective of consumers paint a different picture. Although there are differences across countries, by and large market concentration has been stable over time, and there is no evidence for a global trend of rising market concentration. This finding is consistent with the role of globalization: although producers might specialize and market concentration might increase across producers in each country, global competition remains substantial; hence the global market does not become more concentrated, and in practice consumers do not face a restricted set of suppliers.

In ongoing work, we estimate a CES demand system and a simple model following Atkeson and Burstein (2008) to estimate markups using our consumption data. This structural approach complements the reduced-form facts on market concentration.

IV Quality-Adjusted Cross-country PPP

In the second part of the paper, we build purchasing power parity (PPP) indices using identical barcodes across countries. A key advantage of our data is that we can compare identical barcodes across countries. For brevity, we describe in detail the results for the comparison between two countries, Italy and Germany.

IV.A The Gerschenkron effect across countries

We first focus on the set of barcodes we can match across Germany and Italy. We examine the extent to which PPP comparisons are sensitive to the weighting scheme used to compute the PPP index. We seek to answer the following question: what is the increase in cost of livig for a household going from Germany to Italy? Conceptually, this analysis is similar to the exercise in Section 3, except that the comparison is conducted across countries rather than within countries over time. The price indices are compted in the same way as defined in Section 3, except that t corresponds to Germany and $t+1$ to Italy.

The results for Italy and Germany are reported in panel (a) of Figure 7. According to the Paasche index, which uses the expenditure weights observed in Italy, Italy is 21.3% cheaper than Germany. In contrast, with the Laspeyres index, which uses the expenditure weights observed in Germany, Italy is 8.5% more expensive than Germany. This variability is not surprising: because of substitution bias, indices can be sensitive to the weighting scheme. The large difference between the Laspeyres and Paasche indices indicate that, in practice, the results are very sensitive to the choice of weights. But it is reassuring to see that superlative indices - Fisher, Tornqvist and CES - all give a similar picture: the cost of living in Italy is about 7% to 8% lower in Italy than in Germany.

Panel (a) of Figure 7 also reports the results of a simple average. The simple average does not use weights and reflects the methodology of international statistical agencies, which do not have access to barcode-level expenditure are can only match products without ascribing them specific weights. This PPP index indicates that Italy is 4.2% cheaper than Germany. This difference in cost of living is significantly attenuated relative to the true PPP difference, which is captured by the superlative indices.

IV.B Product variety bias across countries

Next, we compute PPP indices accounting for the fact that the range of available products varies across countries. We do so using the CES framework described in Section 3. The results are reported in panel (a) of Figure 7: we find that accounting for differences in product variety makes a large difference. Product variety is much larger in Germany, which lowers the cost of living in Germany relative to Italy. Once this is taken into account, the cost of living in Italy is 14.9% higher than in Germany.

This results shows that the product variety adjustment is large enough to flip the sign a the PPP adjustment. With CES on continued products alone, Italy appears to be cheaper than Germany. But once product variety is accounted for, Italy becomes effectively more expensive than Germany. To the best of our knowledge, this paper is the first to document that cross-country difference in product variety have have a large impact on PPP indices.

The magnitude of the adjustment for product variety depends on the elasticity of substitution between products. In Panel (b) of Figure 7, we show that, across the range of plausible elasticities documented in the literature (e.g, Broda and Weinstein (2010)), the finding described above is robust. It is always the case that the sign of the PPP adjustment flips from negative without the product variety adjustment (which corresponds to an infinite elasticity of substitution) to positive with the product variety adjustment (considering elasticity of substitution from 5 to 9). Conceptually, the higher the elasticity of substitution, the smaller the adjustment because there is less infra-marginal consumer surplus created by the entry of new goods.

IV.C Non-homothetic PPP and household heterogeneity

In this section, we produce PP indices across the income distribution between Italy and Germany. We find that PPP indices between countries vary significantly depending on which household income serves as the reference level.

IV.C.1 Theory

We consider the non-separable class of CES functions in Hanoch (1975), Comin et al. (2020), and Matsuyama (2019). We observe data on households indexed by h that differ in income and total expenditures E_t^h. The non-homothetic CES consumption index for household h is implicitly defined by

$$\sum_{k\in\Omega_t}\left(\frac{\varphi_{kt}^h c_{kt}^h}{\left(C_t^h\right)^{(\varepsilon_k-\sigma)/(1-\sigma)}}\right)^{(\sigma-1)/\sigma} = 1$$

where c_{kt}^h denotes household h consumption of product k at time t, φ_{kt}^h is household h's taste parameter, σ is the constant elasticity of substitution between varieties, and ε_k is the constant elasticity of consumption of product k with respect to the consumption index C_t^h, which allows preferences to be non-homothetic. Homothetic CES is a special case of this utility function, with $\epsilon_k = 1$ for all k.

With $\sigma > 1$, the consumption index C_t^h is globally monotonically increasing and quasi-concave if and only if $\varepsilon_k < \sigma$. Ω_t is the set of varieties available at time t. It is useful to note that the consumption index C_t^h cannot have a cardinal interpretation, because observed demand is invariant to any monotonic transformation $g(C_t^h)$. We return to this point below.

The price index P_t^h is defined by $E_t^h = P_t^h C_t^h$, i.e. it is the mapping from nominal expenditures E_t^h to the real consumption index. It can be interpreted as the average cost of one unit of the real consumption index. With non-homothetic utility, this average cost can vary with the level of the real consumption index.

Consumer optimization yields the following formula for the expenditure share of household h on product k at time t:

$$s_{kt}^h = \frac{\left(p_{kt}/\varphi_{kt}^h\right)^{1-\sigma}\left(E_t^h/P_t^h\right)^{\epsilon_k - 1}}{\left(P_t^h\right)^{1-\sigma}}$$

It can be shown that the non-homothetic price index for each household can be computed as

$$\frac{P_t^h}{P_{t-1}^h} = \left(\frac{\tilde{p}_t}{\tilde{p}_{t-1}}\right)^{\frac{1}{1+\nu}} \left(\frac{\widetilde{s_t^h}}{\widetilde{s_{t-}^h}}\right)^{\frac{1}{(\sigma-1)(1+\nu)}} \left(\frac{E_t^h}{E_{t-1}^h}\right)^{\frac{\nu}{1+\nu}}, \tag{2}$$

with $\tilde{p}_t = \left(\Pi_{k\in\Omega_t^*} p_{kt}\right)^{1/N_t^*}$, where $N_t^* = |\Omega_t^*|$ is the number of common varieties across periods, and $\nu = \frac{1}{N_t^*}\sum_{k\in\Omega_t^*}\frac{\epsilon_k - 1}{1-\sigma}$. This expression shows that the change in the household's cost of living $\frac{P_t^h}{P_{t-1}^h}$ depends directly on the change in income (and hence total expenditure, $\frac{E_t^h}{E_{t-1}^h}$) of the household, as long as preferences are non-homothetic ($\nu \neq 0$).

This result suggests that the price index should be adjusted as agents' income change, simply because the average cost of utility changes with the level of income, through the curvature of the utility function. The micro-foundation of the price index in a non-homothetic utility function, which by definition must have curvature, necessarily yields this result. Is this price index a useful guide to welfare comparisons?

Intuitively, we would want the price index to retain an interpretation as a "money-metric," even with non-homotheticities. The term $\left(\frac{E_t^h}{E_{t-1}^h}\right)^{\frac{\nu}{1+\nu}}$ in the expression above effectively computes the change in the average cost of utility as agents' incomes change. We find this an unsatisfying guide to welfare comparisons over time or across countries, because the change in cost of living measured in this way fundamentally depends on the cardinal interpretation of the real consumption index C_t^h. For example, because Germany is richer than Italy $\left(E_{Germany}^h > E_{Italy}^h\right)$, equation (2) implies that non-homotheticities mechanically increase the cost of living in Italy if $\frac{\nu}{1+\nu} > 0$, or mechanically decrease if $\frac{\nu}{1+\nu} < 0$. As a result, the PPP index would be different from one even if all prices were identical in Germany and Italy, which is clearly an undesirable property and is entirely driven by a cardinal interpretation of the real consumption index.[6] This cardinal interpretation is not grounded in data, because Marshallian demand is invariant to any monotonic transformation $g(C_t^h)$.[7]

Instead, we propose an alternative approach that retains a money-metric interpretation and allows for the computation of PPP indices along the income distribution. We do so by building on Comin et al. (2020), who define a non-homothetic preference aggregator C^ψ which is a monotonic transformation of the real consumption inde with respect to a vector of weights ψ_i summing to one over all goods i.[8] We define

$$\begin{aligned}\epsilon_i^\psi &= \frac{\varepsilon_i}{\sum_j \psi_j \varepsilon_j}\\ \widetilde{\Omega}_i &= \Omega_i / \left(\Pi_j \Omega_b^{\psi_j}\right)^{\varepsilon_i/(\sum_j \psi_j \varepsilon_j)}\end{aligned}$$

This ψ-index of real consumption for household h can be written in terms of observed data as:

$$log(C_h^\psi) = log(E_h) - \sum_{i=1}^{I} \psi_i log(p_i^h) + \frac{1}{1-\sigma} \sum_{i=1}^{I} \psi_i log(\omega_i^h) \quad (3)$$

The corresponding ψ price index for E_h is

$$\begin{aligned}P_h^\psi C_h^\psi &= E_h\\ log(P_h^\psi) &= log(E_h) - log(C_h^\psi)\\ &= \sum_{i=1}^{I} \psi_i log(p_i^h) + \frac{1}{\sigma-1} \sum_{i=1}^{I} \psi_i log(\omega_i^h) \quad (4)\end{aligned}$$

We use this expression to compare welfare across countries. When ψ_i corresponds to the average expenditure shares on the common goods i across the two countries being compared, the first term corresponds to a Tornqvist index. The second term adjusts for changes in product variety and non-homotheticities, as ω_i^h may vary with households' expenditure levels.

This approach have two main advantages for our purposes. First, we will be able to assign positive weights ψ_i only on the set of goods that have identical barcodes across countries. This defines

[6]For example, this point applies to the calculation of a PPP index for a representative consumer in the United States versus Mexico in Argente et al. (2019).

[7]To see why this observation matters for the price index, assume that the welfare-relevant real consumption index is $\tilde{C}_t^h$, such that $g(\tilde{C}_t^h) = C_t^h$, with g a monotonic transformation. We would like the price index $\widetilde{P}_t^h$ to be defined as the mapping from observed expenditure to this welfare-relevant real consumption index, i.e. $E_t^h = \widetilde{P}_t^h \tilde{C}_t^h = \widetilde{P}_t^h g^{-1}(C_t^h)$. For a given set of prices, we can always pick a monotonic transformation $g(.)$ such that $\frac{C_t^h}{g(C_t^h)} \frac{g(C_{t-1}^h)}{C_{t-1}^h} = \left(\frac{E_t^h}{E_{t-1}^h}\right)^{-\frac{\nu}{1+\nu}}$. In this way, we have eliminated the curvature from non-homothetic utility in equation (2). Likewise, we could pick $g(.)$ to move $\frac{P_t^h}{P_{t-1}^h}$ arbitrarily through the third term in (2). This shows that the cardinal interpretation is not tenable for PPP measurement, because it is not disciplined by data.

[8]See Appendix A.2.2 in Comin et al. (2020).

the real consumption index in terms of comparable goods and alleviates concerns over unobserved quality differences, while allowing us to make a general statement about welfare across countries according to a micro-foundation. Second, the PPP indices retain a money-metric interpretation. Using equation (2) we can compute the price index at different levels of utility, and we know the mapping from observed expenditure to utility from equation (3). For each level of expenditure observed in the reference country, we can compute the change in expenditures that would be required to attain the same level of utility in the comparison country (under the assumption that there is no unobserved quality differences across goods with common barcodes). Considering Italy and Germany, it can be shown that the expenditure ratio for utility level U is:

$$\frac{e(p_{Italy}, U)}{e(p_{Germany}, U)} = \frac{P^{\psi}_{h(U,Italy)}}{P^{\psi}_{h(U,Germany)}} \tag{5}$$

This ratio is invariant to any monotonic transformation $g(.)$ of the real consumption index, as desired. This ratio can be alternatively interpreted as the willingness to pay of Italian households with utility level U for facing German prices and product variety, expressed as a fraction of their nominal expenditures. This provides an intuitive meaning for the non-homothetic PPP index, which is effectively a measure of compensating variation holding utility fixed at the reference level. A key question is whether the PPP index varies across the household distribution - if so, PPP indices cannot be easily summarized by a single country-level index as in common practice.

IV.C.2 Results

We compute the PPP indices for German and Italian households using the formula in (5). We present the results along the household expenditure distribution in Italy.[9] Our baseline results use $\sigma = 6$, as previously, and we set ψ_i to the average expenditure shares on the common goods i across the two countries.

Panel (a) of Figure 8 reports the main results. The x-axis corresponds to the deciles of expenditure across Italian households. The y-axis given the PPP index, which can also be interpreted at the willingness to pay of Italian households for German prices and product variety. The estimates account for product variety, which tends to be higher in Germany, therefore Italy is more expensive than Germany for all households - about 12% more expensive on average, which is similar to Figure 5. Interestingly, the figure shows that the PPP index varies significantly depending on what

[9] There is a one-to-one relationship between the rank of households in the expenditure and utility distributions. Given our focus on money-metric results, we discuss the results along the expenditure distribution, but they can be thought of in an equivalent way along the utility distribution.

utility/expenditures level is considered. For Italian household at the bottom of the income distribution, Italy is about is close to 13% more expensive than Germany. In contrast, for households in the fourth quintile of the distribution, Italy is only 9% more expensive. The differences increases again at higher levels of expenditure, reaching about 12.5% at the top of the distribution. These differences are large: PPP indices are over 40% larger for households at the top and bottom of the income distribution, compared with PPP for the middle class.

Panel (b) of Figure 8 conducts sensitivity tests, depending on the value of σ. As σ increases, the PPP index for Italy relative to Germany increases further, as in Figure 7, because product variety is valued more. For lower values of σ, the differences in PPP across the distribution are weakened. When σ is infinite, the PPP index is effectively a Tornqvist index over the set of common barcodes, which falls below zero and is by definition identical across the income distribution. These results highlight that parametrizing σ accurately is essential. In the relevant range of σ, accounting for non-homotheticicities appears to be important.

To the best of our knowledge, this paper is the first to establish the quantitative importance of heterogeneity along the income distribution for the computation of PPP indices.[10] In ongoing work, we also document household-level heterogeneity in PPP, accounting for preference heterogeneity beyond the component systematically linked to income.

IV.D Accounting for taste heterogeneity across countries

We compute price indices which allow for taste differences across countries, which standard PPP indices cannot do, and find that taste differences significantly affect PPP indices worldwide. To the best of our knowledge, there exists no estimate of the importance of taste heterogeneity across countries for PPP estimation.

We follow the methodology of Redding and Weinstein (2020), which derive the CES price index with taste shocks to compute inflation over time within a country. Applied to our cross-country setting, taste shocks mean that tastes in Italy are allowed to be different from Germany across varieties, although the average taste shock is zero. Although taste variability across countries is plausible, there has been no attempt in prior work to adjust PPP indices for cross-country taste heterogeneity.

[10]Prior has examined the role of non-homotheticicities using representative agents in each country, along with a cardinal interpretation of the utility function.

The formula is as follows:

$$\Sigma^{CES} = \frac{\widetilde{p_t}}{\widetilde{p_{t-1}}} \cdot \left(\frac{\widetilde{s_t}}{\widetilde{s_{t-1}}} \right)^{\frac{1}{\sigma-1}} \cdot \left(\frac{\lambda_t}{\lambda_{t-1}} \right)^{\frac{1}{\sigma-1}},$$

where $\tilde{x}$ denotes the geometric mean of x. λ_t denotes the aggregate share of common varieties in total expenditures, and the term $\left(\frac{\lambda_t}{\lambda_{t-1}}\right)^{\frac{1}{\sigma-1}}$ is the standard correction for product variety, as in Feenstra (1994). $\frac{\widetilde{p_t}}{\widetilde{p_{t-1}}}$ is the geometric mean of price relatives for common varieties. The term $\left(\frac{\widetilde{s_t}}{\widetilde{s_{t-1}}}\right)^{\frac{1}{\sigma-1}}$ depends on the geometric mean of relative expenditure shares for common varieties in the two time periods. This second component captures changes in the degree of heterogeneity in taste-adjusted prices across common varieties. The intuition is that consumers value dispersion in taste-adjusted prices across varieties if these varieties are substitutes ($\sigma > 1$). The reason is that they can substitute away from varieties with high taste-adjusted prices and toward varieties with low taste-adjusted prices. In our cross-country comparison of Italy, as above t corresponds to Germany and $t+1$ to Italy.

Figure 9 reports the results with taste shocks. We find that allowing for taste shocks considerably lower the PPP adjustment. This results mean that prices tend to be systematically lower for goods which Italian households have a stronger preference for. It is instructive to think through the sense in which the results in panel (e) may be a more accurate summary of cost of living differences. There are two cases to distinguish between, which call for different PPP calculatons. First, taste differences across households of different nationalities may be a permanent feature. If a German household moves to Italy, they may keep the same baseline German tastes. In that case, the result with the product variety adjustment in panel (a) of Figure 7 is the desired PPP adjustment for German households. But if one wishes to estimate the cost of achieving different levels of utility in different countries, it is important to adjust for taste differences as in Figure 9, because the price index in a country depends on the distribution of tastes in that country.

In ongoing work, we study the persistence of taste differences across countries and compute PPP indices for the two distinct purposes described above.

IV.E Extensions

We conclude this section with a brief discussion of several extensions. First, to assess the importance of matching exactly the same barcodes, rather than doing approximate comparisons, we compare our baseline results in Figure 7 to the results we obtain when matching goods produced by the same manufacturer (but which do not necessarily have the same barcodes). The results are reported in

Figure 10. The patterns are markedly different, with superlative PPP indices (Fisher, Tornqvist, CES) close to -12% in Figure 10, instead of -7% in Figure 7. Moreover, the correction for product variety still makes Germany relatively cheaper than Italy, but barely so. This analysis indicates that it is important to match exactly the same barcodes: the scope for quality bias is large, even within identical manufacturers.[11]

V Implications for International Real Income Inequality

In this section, we then study whether the PPP biases documented in the previous subsection relate systematically to the level of economic development and assess how they affect international real income inequality, as in Almås (2012).

We find that our PPP indices, using either FMCG or SMCG scanner data, imply considerably larger international inequality than the standard ICP/PWT PPP index. Compared with standard PWT incomes (Feenstra et al. (2015)), we find that estimates of real incomes based on exchange rates (which implicitly assume that PPP holds) are closer to our estimates with PPP indices from scanner data. These results suggest that standard PPP indices undersestimate the price level in low-income and more populated countries and overestimate it in high-income and less populated countries, thus underestimating international inequality and overestimating world GDP per capita.

V.A Methodology

We use the SMCG and FMCG datasets to compute CES PPP indices, with or without product variety adjustment, in the sample of countries for which we can match identical barcodes.[12] The SMCG sample includes 24 countries, covering a large set of countries, with GDP per capita ranging from about €5,000 to about €80,000.[13] The FMCG sample covers 14 countries, including 13 EU members states.[14]

For each country, we compute the price level relative to Germany assuming a representative agent with CES preferences, using the set of identical barcodes in the two countries, as in equation

[11] In ongoing work, we estimate the extent to which the law of one price holds across countries and by household groups. We find that there are significant departures from the law of one price, including within the eurozone. Compared to prior work, this analysis isolates deviations from the law of one price after accouting for potential heterogeneity in heterogeneous price elasticities across countries and household groups.

[12] We extend this sample in ongoing work.

[13] The SMCG sample includes Australia, Austria, Belgium, Brazil, Chile, China, Czech Republic, Finland, France, Germany, India, Italy, Japan, Netherlands, Norway, Poland, Portugal, Russia, South Korea, Spain, Sweden, Switzerland, Turkey, United Kingdom.

[14] The FMCG sample includes Austria, Belgium, Czech Republic, Denmark, France, Germany, Hungary, Italy, Netherlands, Poland, Romania, Russia, Slovakia, Sweden.

1 (where t indexes the reference country, Germany, and $t + 1$ indexes the comparison country). We compare the PPP indices obtained with scanner data with the PPP indices of the International Comparison Program (ICP) of the World Bank, which is used to compute estimates of real income in the Penn World Tables (PWT). In particular, we assess the extent to which the PPP corrections vary with the level of economic development and draw implications for real income inequality across countries. We draw these comparisons after adjusting prices for the nominal exchange rate.

V.B Results

Results for slow-moving consumer goods. The results for slow-moving consumer goods are shown in Figure 11, with the OLS coefficients for the lines of best fit reported in Table 2.

Panel A of Figure 11 depicts the cross-country relationship between the ICP PPP adjustment and real GDP per capita, as reported in the Penn World Tables. The figure shows is a strong positive relationship, i.e. low-income countries benefit from lower prices according to the ICP price index. For example, after adjusting for the nominal exchange rate, the real price level in India is about 60% lower than in Germany, about 25% lower for China, and about 40% larger for Norway and Switzerland. The regressions results are reported in Column (1) of Table 2, with an increase if the ICP price index of 0.1447pp (s.e. 0.03) per €10,000 increase in country GDP.

Panel B shows the results using the CES price index for identical barcodes to compute the PPP adjustment. The positive relationship between GDP per capita and the price level largely disappears, with an OLS coefficient of 0.02427 (s.e. 0.0117) in Column (3) of Table 2. The price level in India is only about 10% smaller than in Germany and is very similar to the price level in Switzerland.

Panel C shows the results using the full CES price index, computed over identical barcodes and accounting for differences in product variety. There is no longer a significant relationship between the real price level and GDP per capita, with an OLS coefficient of 0.01215 (s.e. 0.03469) in Column (5) of Table 2. With the adjustment for product variety, the real price level for India is now about 10% *higher* than in Germany, while the price index in Switzerland is about 20% higher than in Germany.

Results for fast-moving consumer goods. The results using the sample of fast-moving consumer goods are reported in Figure 12, with the regression coefficients in Columns (2), (4) and (6) of Table 2. While the sample of countries is not as large as with the slow-moving consumer goods sample, the results are similar. Using the CES price index, panel A depicts a strong positive relationship between the price level and GDP per capita. The relationship turns negative and not significant with the CES prices index over continued goods alone (panel B) as well as when accounting for product variety (panel C).

According to the ICP PPP indices, compared to Germany the real price level is about 50% lower for countries like Romania, Hungary, Poland, and Russia. In contrast, according to our CES index with product variety, the price index is 5 to 20% *higher* in this set of countries compared with Germany.

Implications for the international Gini index and average GDP per capita across countries. The preceding results have quantitatively meaningful implications for international inequality. Indeed, compared with the standard ICP PPP index, we find that the real price level is higher in low-income countries and lower in high-income countres. Table 3 summarizes the implications for the Gini index, with and without population weights across countries.

Columns (1) and (2) report the Gini index using ICP PPP to obtain real income across countries. With population weights, the Gini is 0.37 in the SMCG sample, which covers a large set of countries worldwide, and 0.15 in the FMCG sample, which primarily covers European countries. The Gini increase substantially with the CES index with the correction for product variety, as shown in Columns (3) and (4). The Gini is 0.52 in the SMCG sample, a 40% increase compared with the ICP baseline; the Gini is 0.33 in the FMCG sample, i.e. a 120% increase relative to the ICP baseline. Columns (5) and (6) show that Gini coefficients based on nominal exchange rates only are close to our preferred estimates, at 0.53 in the SMCG sample and 0.31 in the FMCG sample. Thus, according to our estimates, using exchange rates alone provides better estimates of international income inequality than PWT incomes based on ICP PPP indices. The results for the Gini coefficent without population weights are similar.

Table 4 documents the implications of our findings for average GDP per capita across countries. Using ICP PPP, Columns (1) and (2) report that, with population weights, average GDP per capita is €17,178 in the SMCG sample and €36,574 in the FMCG sample. With the CEX index with the correction for product variety, average GDP per capita falls substantially, as shown in Columns (3) and (4). Average GDP per capita falls by 22% to €13,534 in the SMCG sample, while it falls by 19% in the FMCG sample. In Columns (5) and (6), estimates of average GDP per capita using incomes based on exchange rates alone are close to our preferred estimates.

These results suggest that incomes based on exchange rates alone provide a better approximation to real income and its dispersion worldwide than standard PWT incomes based on the IPC PPP index. These findings are consistent with the results of Almås (2012), who used a completely different methodology based on Engel curves for food.[15]

Policy implications. In addition to painting a different picture of average income worldwide and international income inequality, these results have direct policy implications for programs where the allocation of funds across countries are based on PPP incomes. For example, in the wake of the 2020 pandemic, the €750 billion recovery plan "Next Generation EU" uses an allocation scheme across EU members states where a country's share is proportional to the inverse of 2019 real GDP per capita. Using our CES PPP estimates accounting for product variety, Eastern European countries have a lower real GDP per capita than with standard estimates, i.e. their share of funds should increase. For example, for Romania, Hungary, Poland, and Slovakia, the funds should increase by about 40%, i.e. an additional transfer of about 0.60% of GDP for this set of countries. Conversely, the transfer would decrease for Belgium, Denmark, and the Netherlands.

VI External Validity

In ongoing work, we assess the external validity of our findings beyond fast-moving and slow-moving consumer goods.

We first take a structural approach. To address the limitation that only a subset of total expenditures is observed, we use shifts in Engel curves. We do so following recent work by Almås et al. (2018) and Atkin et al. (2020)), which extend the Engel curve method originally developed by Hamilton (2001) and Costa (2001).

Second, to directly check the external validity of our findings, we supplement the scanner data with more aggregate data on prices and expenditures from national statistical agencies covering the full consumption basket of consumers within the eurozone.

VII Conclusion

This paper is the first to use worldwide scanner data to estimate the implications of price heterogeneity for inequality. This dataset provides harmonized barcode-level data on expenditures and prices for fast-moving consumer goods and slow-moving consumer goods during the last decade in

[15] Relative to Almås (2012), (i) we provide direct evidence, based on identical matched barcodes in a wide set of countries, that PWT incomes may be biased upward for low-income countries, and (ii) we find that incomes based on exchange rates may be more accurate than PWT incomes for *both* low-income countries (e.g., India) and high-income countries (e.g., Switzerland). In contrast, Almås (2012) emphasized that exchange rates may provide better estimates than PWT incomes only for low-income countries.

thirty four countries, which represent 70% of world GDP and 60% of world population, and include both developing (e.g., Brazil, China, India, and South Africa) and developed countries (e.g., the United States, Russia, and most European countries). Overall, the findings indicate that global inequality is higher than previously estimated, and that using micro data on prices and expenditures is crucial to accurately describe patterns of inclusive growth worldwide.

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Table 1: 5-digit ECOICOP categories with available scanner data, spending per 1000 euros

ID	(E)COICOP category	4-digit subcategories						Major source
		#	Weight: all	# goods only	Weight: goods only	# covered	Weight covered	
1	Food and non-alcoholic beverages	61	113.42	61	113.42	61	113.42	FMCG
2	Alcoholic beverages, tobacco and narcotics	14	42.06	14	42.06	13	42.06	FMCG
3	Clothing and footwear	12	51.39	10	50.2	0	0	SMCG
4	Housing, water, electricity, gas and other fuels	25	233.06	9	48.74	2	7.04	SMCG
5	Furnishings, household equipment and routine household maintenance	40	56.93	29	51.41	21	26.33	SMCG
6	Health	14	53.83	6	21.85	1	1.5	SMCG
7	Transport	28	152.19	12	88.45	4	8	SMCG
8	Communications	11	29.59	8	2.92	8	27.16	SMCG
9	Recreation and culture	53	114.19	39	57.86	18	31.71	SMCG
10	Education	6	9.31	0	0	0	0	
11	Restaurants and hotels	6	57.67	2	23.82	0	0	
12	Miscellaneous goods and services	33	86.36	9	19.91	8	32.3	SMCG

The table provides an overview of 5-digit subcategories with available scanner data, taking into account both the fast-moving consumer goods (FMCG) scanner data and the slow-moving consumer good (SMCG) scanner data. Entries in the "Goods only" columns refer to the number (and relative importance) of 5-digit ECOICOP subcategories composed of goods only. For illustration, ECOICOP weights for Germany for the year 2020 are provided.

Table 2: Cross-country Relationships between PPP Adjustments and Real GDP

	Price level relative to Germany					
	ICP		CES index, scanner data		CES index with product variety, scanner data	
	(1)	(2)	(3)	(4)	(5)	(6)
Real GDP/10 000 (PWT)	0.1447***	0.2418***	0.02427**	−0.0652	0.01215	−0.017073
	(0.03084)	(0.04184)	(0.01170)	(0.03723)	(0.03469)	(0.04438)
Sample of countries	SMCG	FMCG	SMCG	FMCG	SMCG	FMCG
N	24	14	24	14	24	14

Notes: Robust standard errors are reported in parentheses.

Table 3: Implications for International Inequality

	Gini with ICP PPP		Gini with CES index and product variety from scanner data		Gini with exchange rates	
	(1)	(2)	(3)	(4)	(5)	(6)
Unweighted	0.22547	0.15948	0.35770	0.31772	0.35656	0.29969
Population-weighted	0.37574	0.15476	0.52415	0.33637	0.53660	0.30848
Sample of countries	SMCG	FMCG	SMCG	FMCG	SMCG	FMCG
N	24	14	24	14	24	14

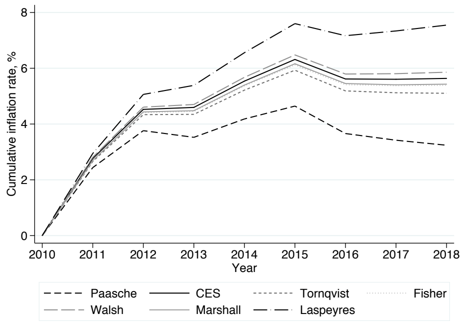
Notes: In all samples, Germany is used as the reference country.

Table 4: Implications for Average GDP per Capita across Countries, 2017 euros

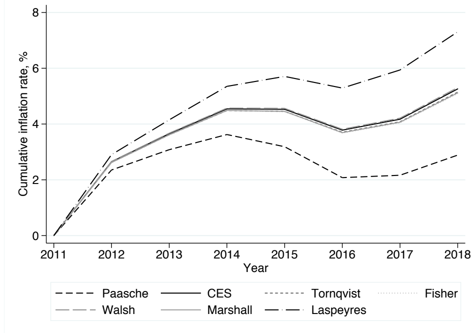
	GDP/capita with ICP PPP		GDP/capita with CES index and product variety from scanner data		GDP/capita with exchange rates	
	(1)	(2)	(3)	(4)	(5)	(6)
Unweighted	40 000	38 083	35 384	34 126	41 303	35 675
Population-weighted	17 178	36 574	13 534	29 698	13 085	31 091
Sample of countries	SMCG	FMCG	SMCG	FMCG	SMCG	FMCG
N	24	14	24	14	24	14

Notes: In all samples, Germany is used as the reference country in 2017.

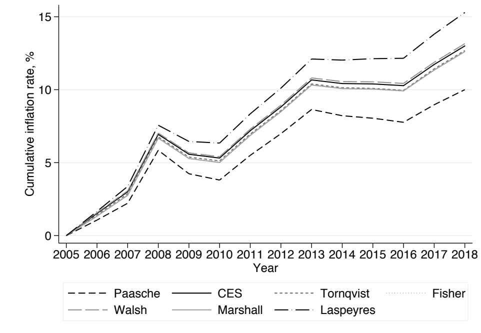
Figure 1: Inflation on Continued Products across Countries, Fast-Moving Consumer Goods



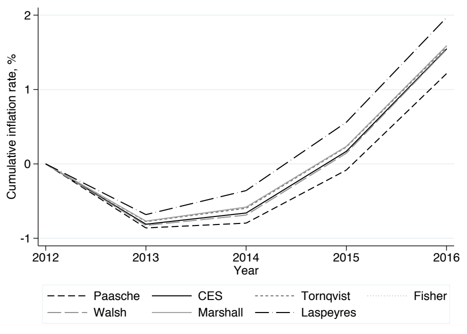
(a) U.S.A., 2010-2018



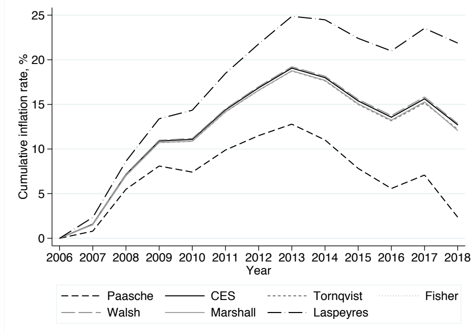
(b) China, 2011-2018



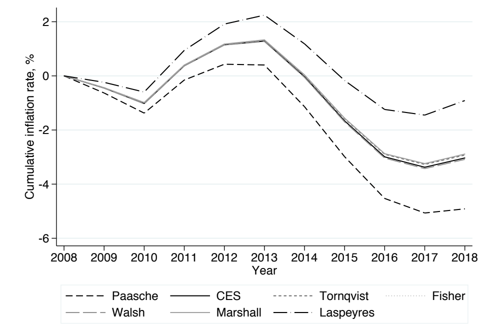
(c) Germany, 2005-2018



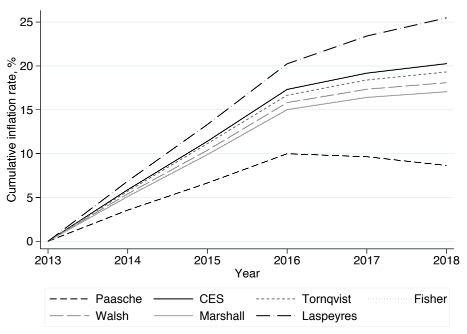
(d) India, 2012-2016



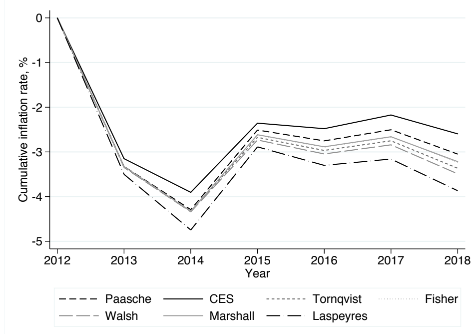
(e) U.K., 2006-2018



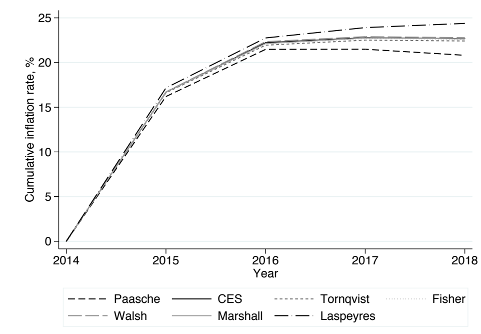
(f) France, 2008-2018



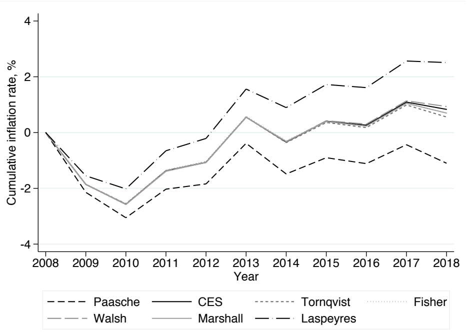
(g) Brazil, 2013-2018



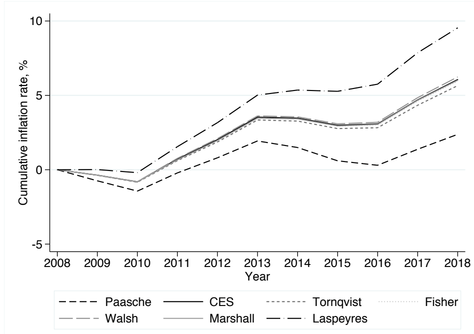
(h) Italy, 2012-2018



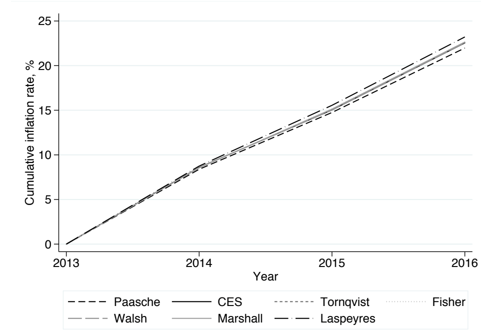
(i) Russia, 2008-2018



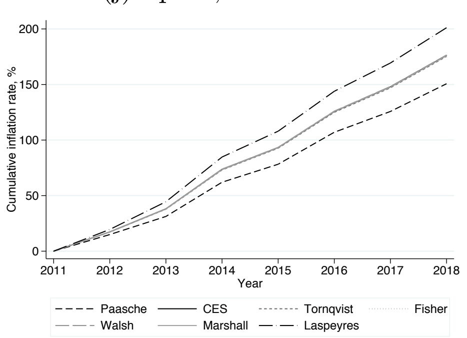
(j) Spain, 2008-2018



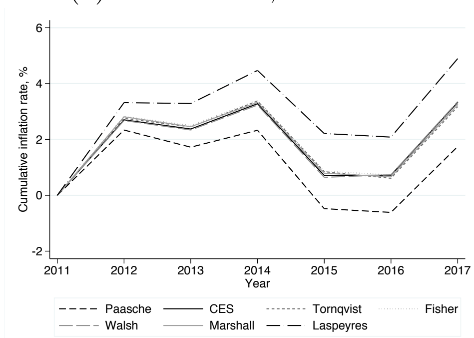
(k) Netherlands, 2008-2018



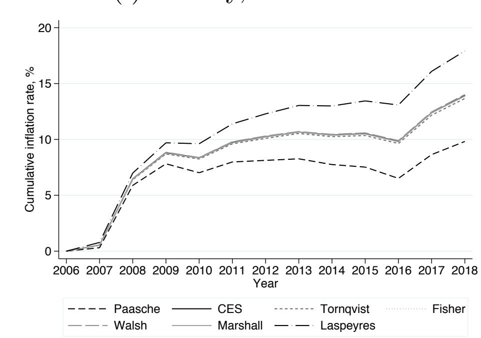
(l) Turkey, 2013-2016



(m) Argentina, 2011-2018



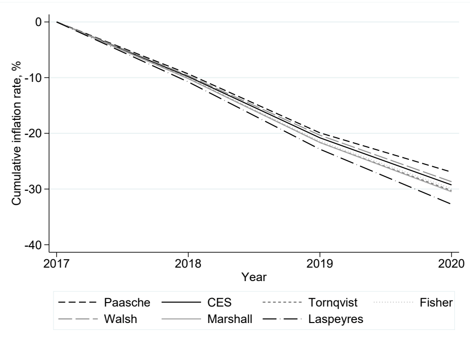
(n) Poland



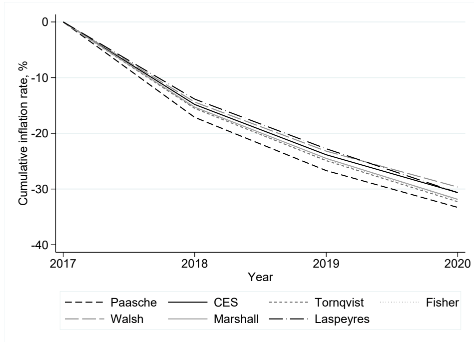
(o) Sweden

Notes: This figure reports inflation on continued products for the 15 largest economies in our sample of fast-moving consumer goods.

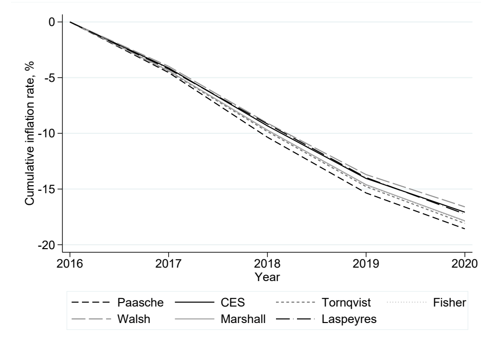
Figure 2: Inflation on Continued Products across Countries, Slow-Moving Consumer Goods



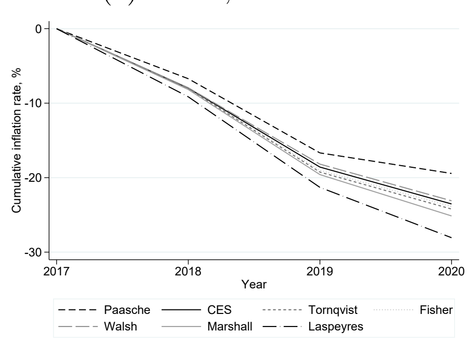
(a) China, 2017-2020



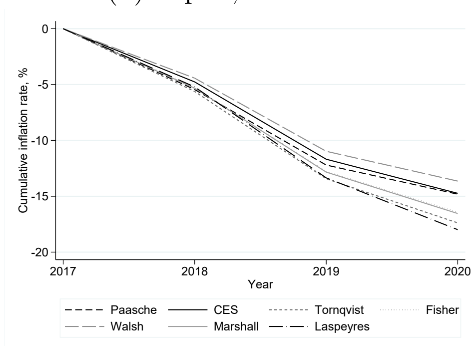
(b) Japan, 2017-2020



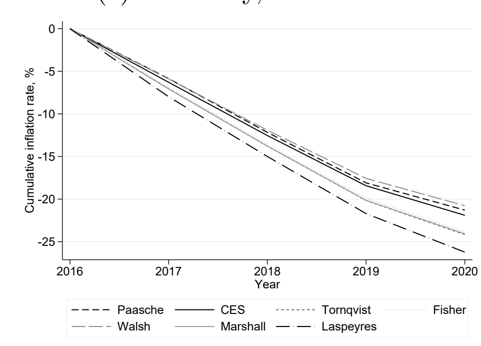
(c) Germany, 2016-2020



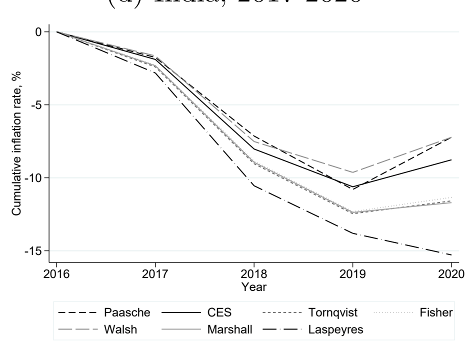
(d) India, 2017-2020



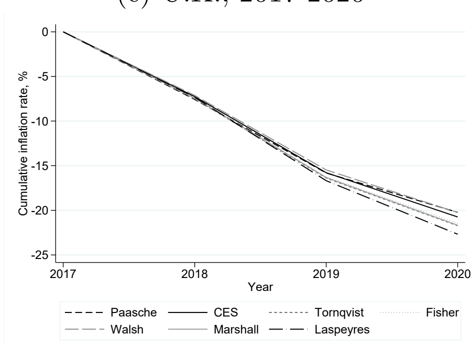
(e) U.K., 2017-2020



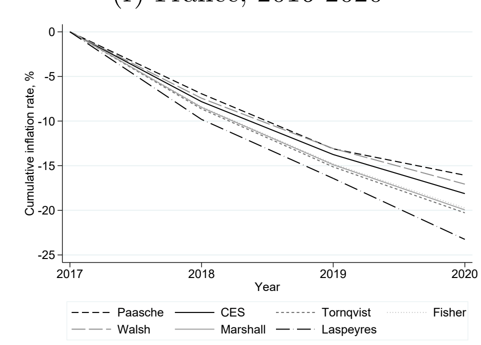
(f) France, 2016-2020



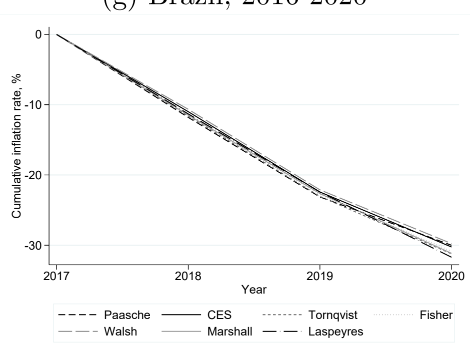
(g) Brazil, 2016-2020



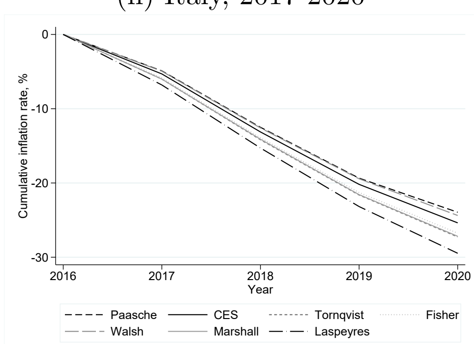
(h) Italy, 2017-2020



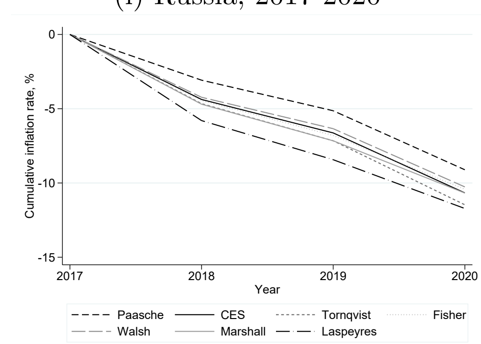
(i) Russia, 2017-2020



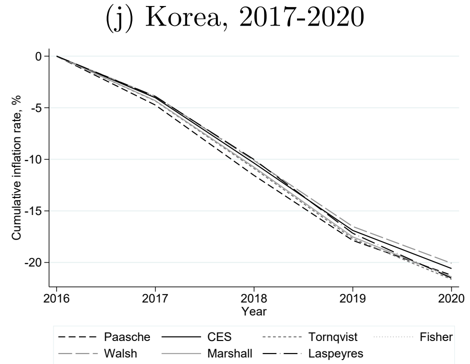
(j) Korea, 2017-2020



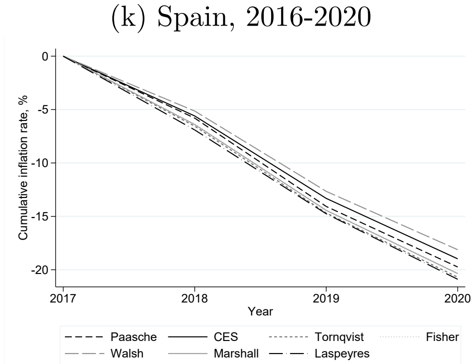
(k) Spain, 2016-2020



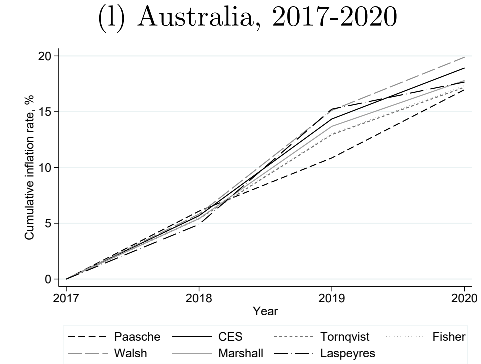
(l) Australia, 2017-2020



(m) Netherlands, 2016-2020



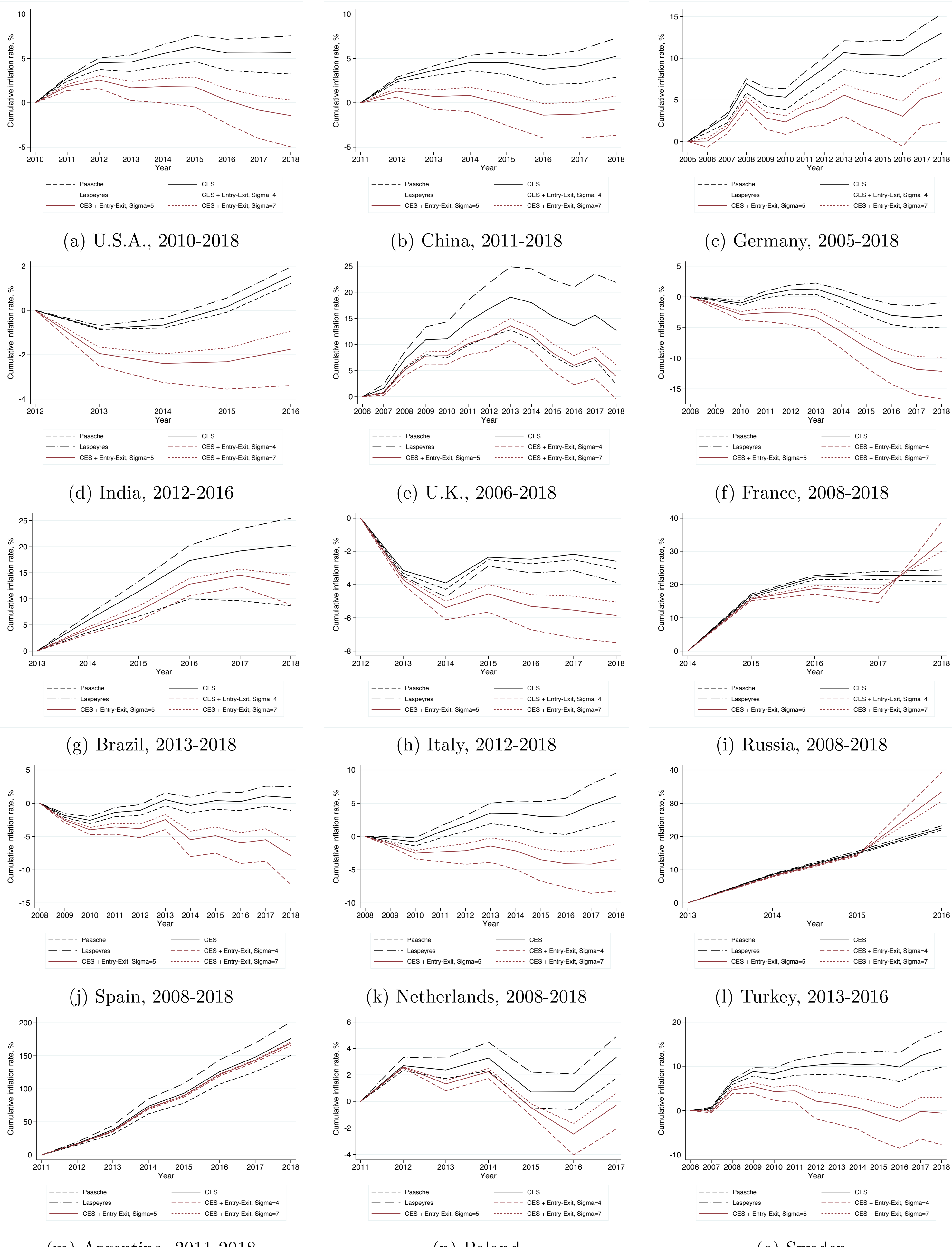
(n) Switzerland, 2017-2020



(o) Turkey, 2017-2020

Notes: This figure reports inflation on continued products for the 15 largest economies in our sample of slow-moving consumer goods.

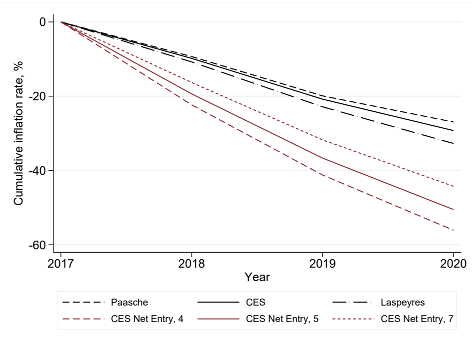
Figure 3: Inflation Adjusted for Changes in Product Variety across Countries, Fast-Moving Consumer Goods



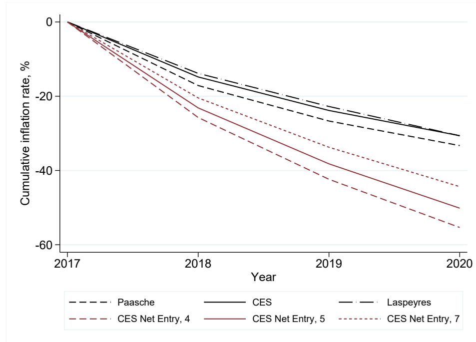
(a) U.S.A., 2010-2018
(b) China, 2011-2018
(c) Germany, 2005-2018
(d) India, 2012-2016
(e) U.K., 2006-2018
(f) France, 2008-2018
(g) Brazil, 2013-2018
(h) Italy, 2012-2018
(i) Russia, 2008-2018
(j) Spain, 2008-2018
(k) Netherlands, 2008-2018
(l) Turkey, 2013-2016
(m) Argentina, 2011-2018
(n) Poland
(o) Sweden

Notes: This figure reports inflation adjusted for changing product variety for the 15 largest economies in our sample of fast-moving consumer goods.

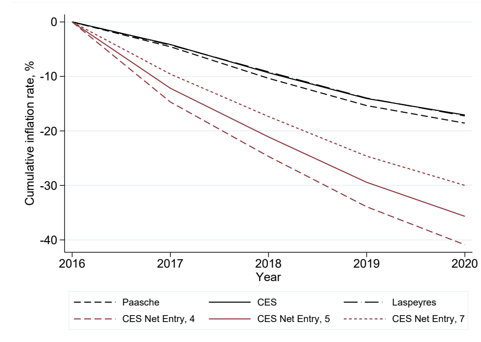
Figure 4: Inflation Adjusted for Changes in Product Variety across Countries, Slow-Moving Consumer Goods



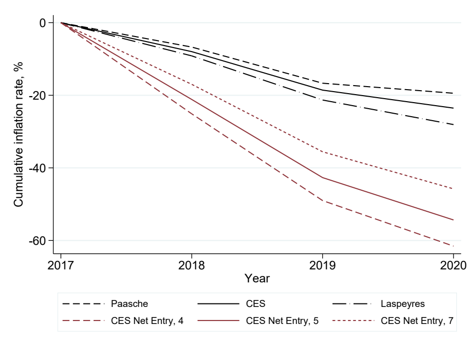
(a) China, 2017-2020



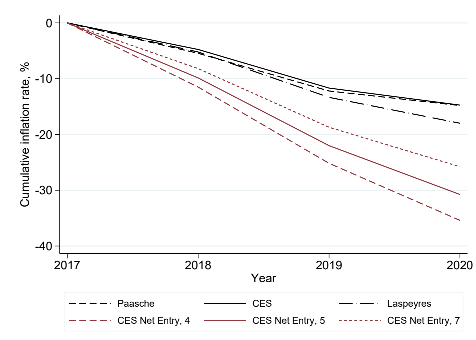
(b) Japan, 2017-2020



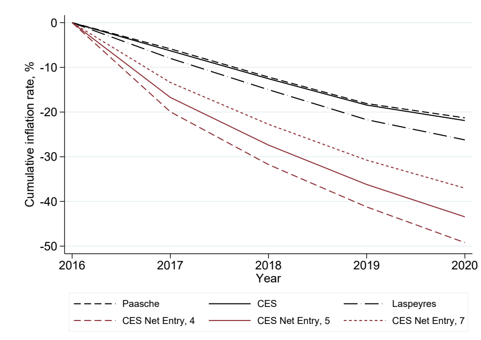
(c) Germany, 2016-2020



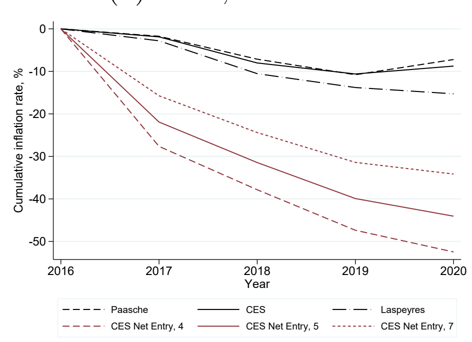
(d) India, 2017-2020



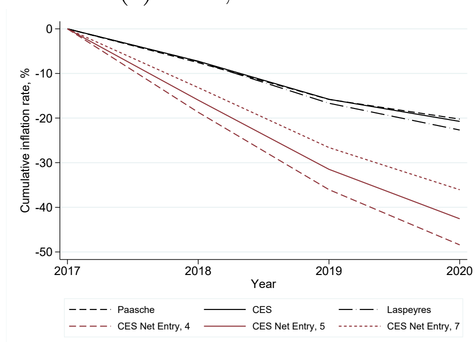
(e) U.K., 2017-2020



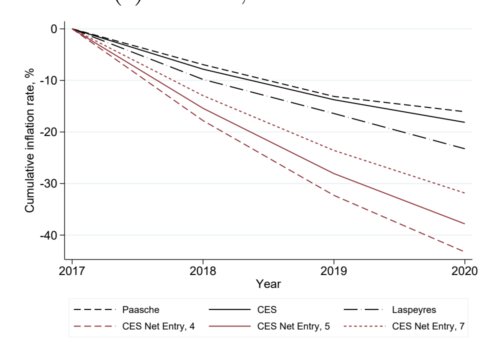
(f) France, 2016-2020



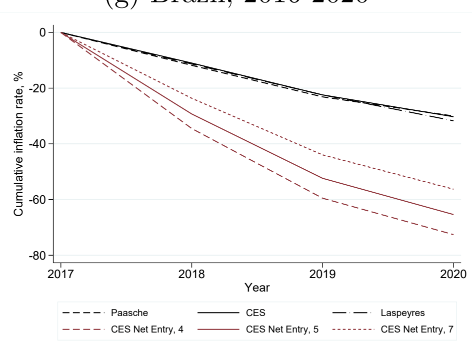
(g) Brazil, 2016-2020



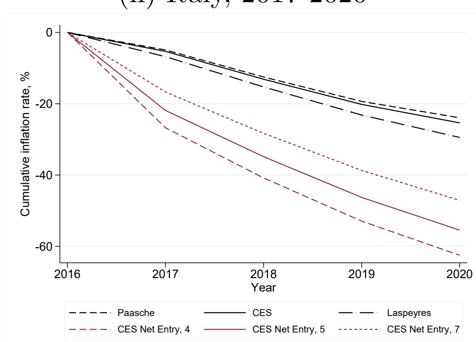
(h) Italy, 2017-2020



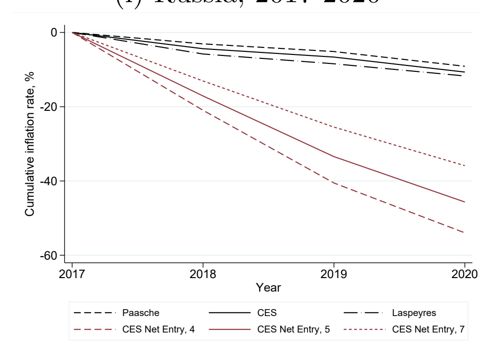
(i) Russia, 2017-2020



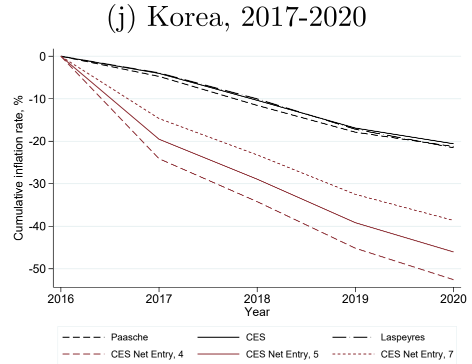
(j) Korea, 2017-2020



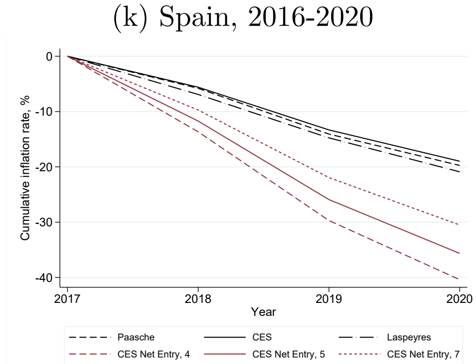
(k) Spain, 2016-2020



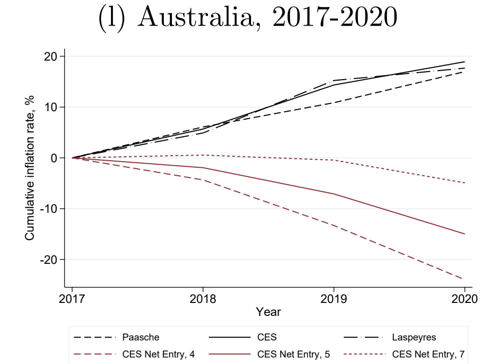
(l) Australia, 2017-2020



(m) Netherlands, 2016-2020



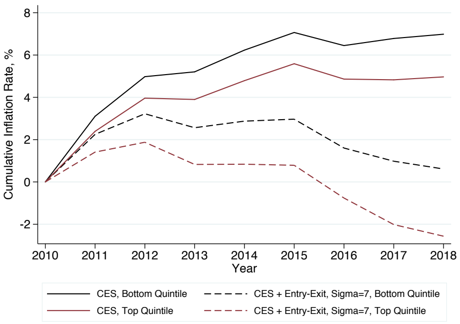
(n) Switzerland, 2017-2020



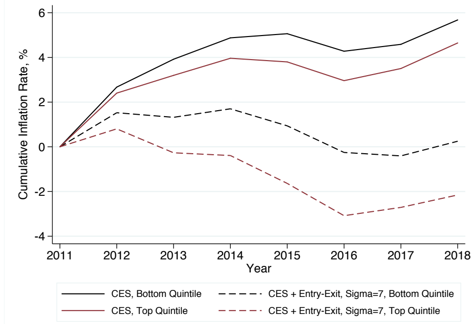
(o) Turkey, 2017-2020

Notes: This figure reports inflation on continued products for the 15 largest economies in our sample of slow-moving consumer goods.

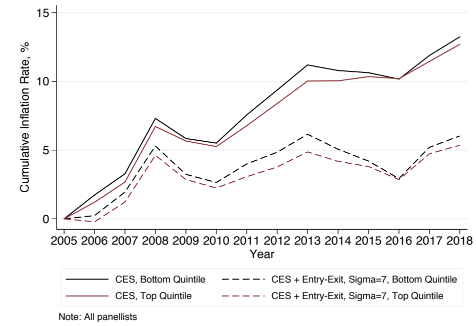
Figure 5: Inflation Inequality b/w Top and Bottom Income Quintiles



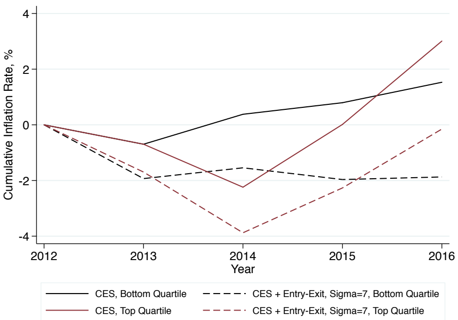
(a) U.S.A., 2010-2018



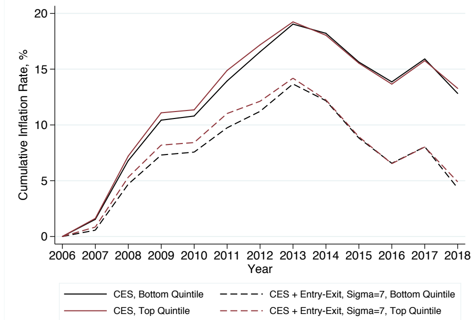
(b) China, 2011-2018



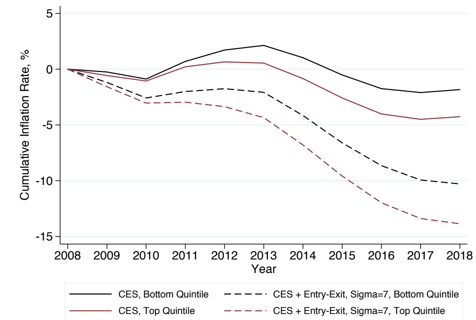
(c) Germany, 2005-2018



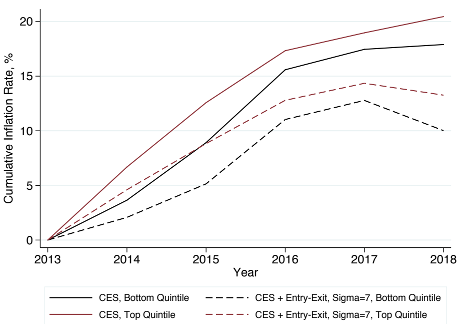
(d) India, 2012-2016



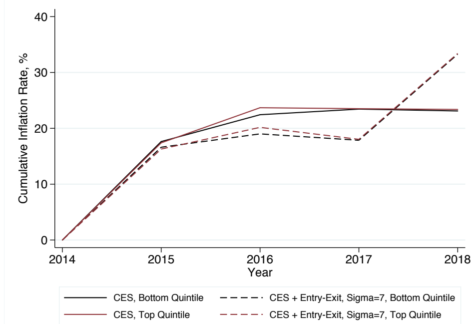
(e) U.K., 2006-2018



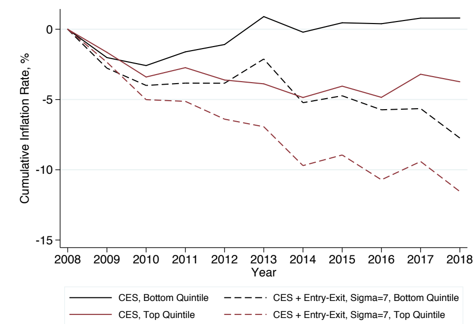
(f) France, 2008-2018



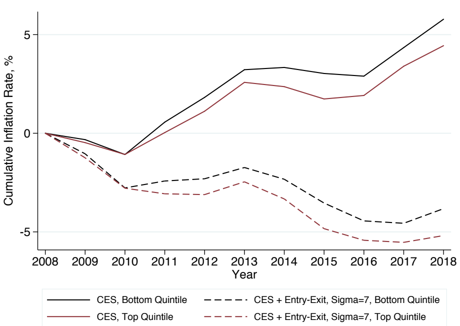
(g) Brazil, 2013-2018



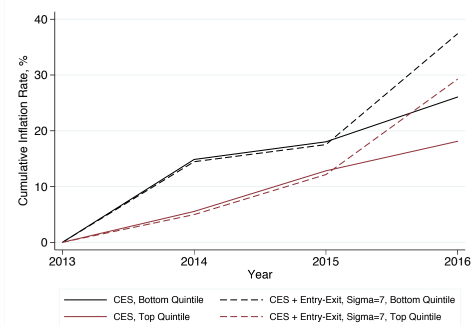
(h) Russia, 2008-2018



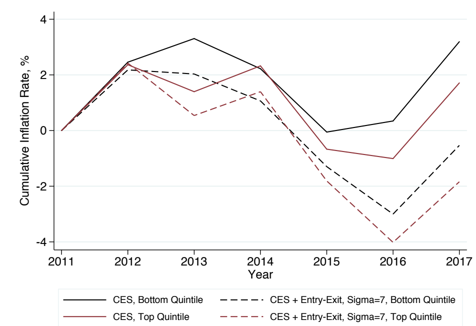
(j) Spain, 2008-2018



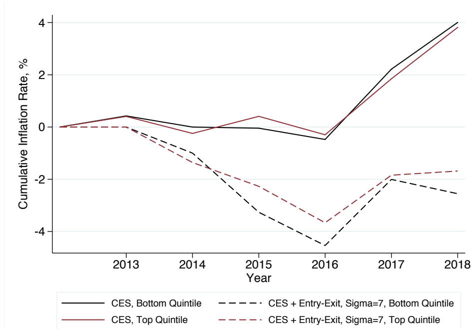
(k) Netherlands, 2008-2018



(l) Turkey, 2013-2016



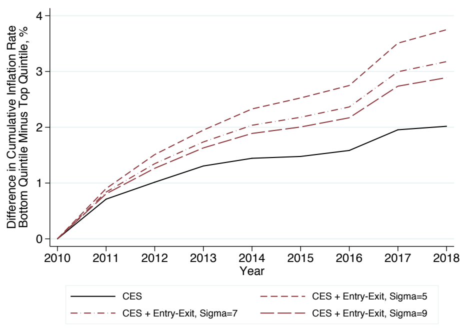
(n) Poland



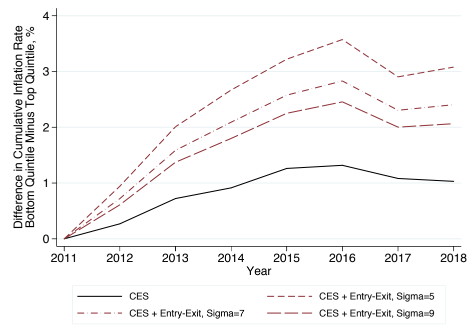
(o) Sweden

Notes: This figure reports inflation inequality on continued products for the 13 largest economies in our sample where socio-demographic information are available.

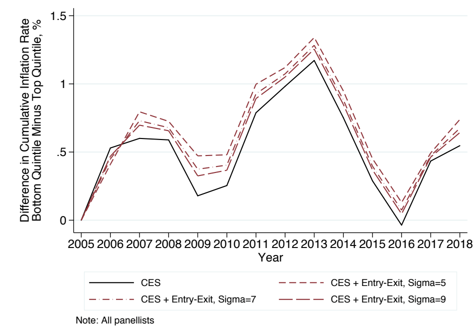
Figure 6: Inflation Inequality b/w Top and Bottom Income Quintiles, Sensitivity Analysis



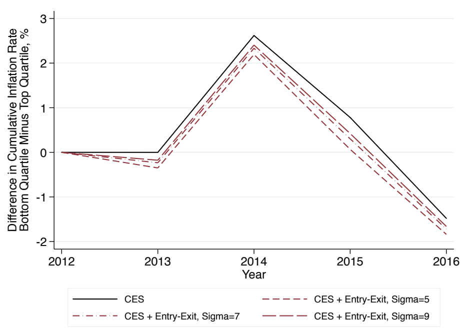
(a) U.S.A., 2010-2018



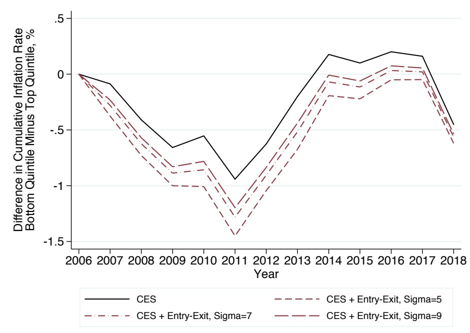
(b) China, 2011-2018



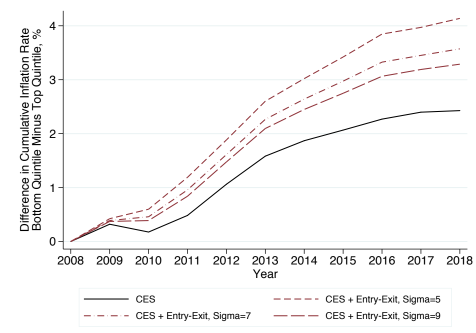
(c) Germany, 2005-2018



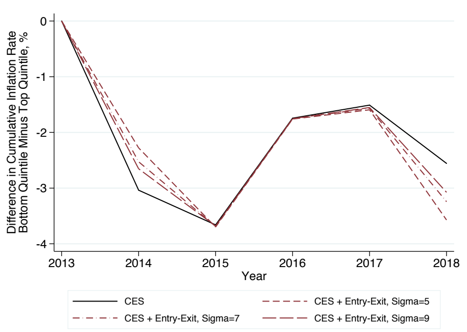
(d) India, 2012-2016



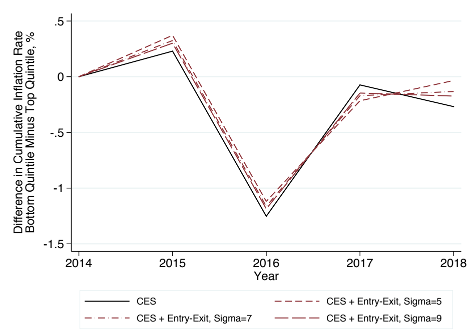
(e) U.K., 2006-2018



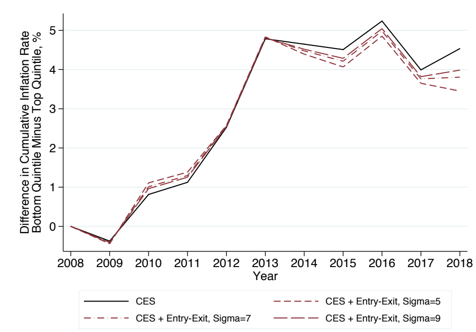
(f) France, 2008-2018



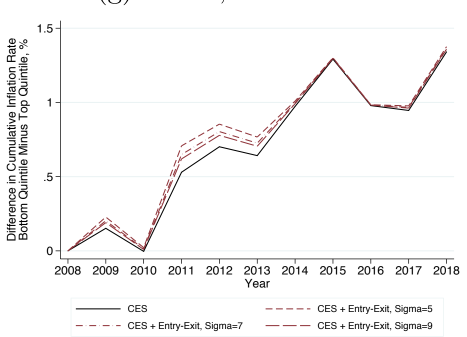
(g) Brazil, 2013-2018



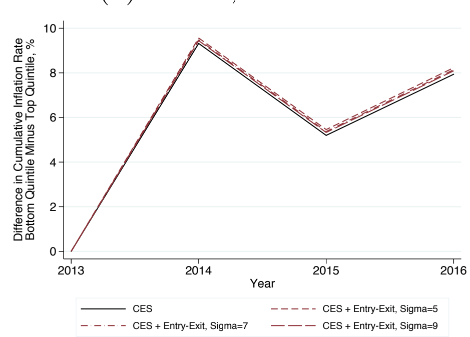
(h) Russia, 2008-2018



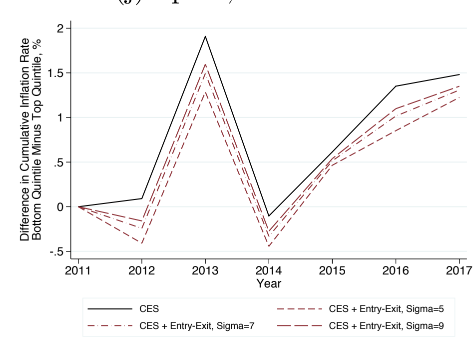
(j) Spain, 2008-2018



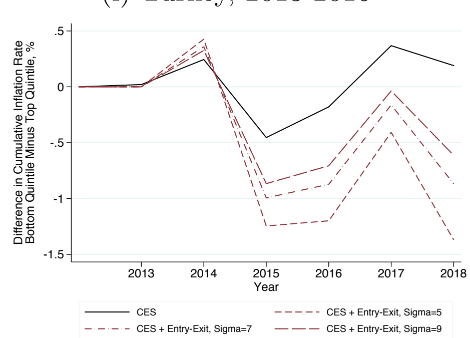
(k) Netherlands, 2008-2018



(l) Turkey, 2013-2016



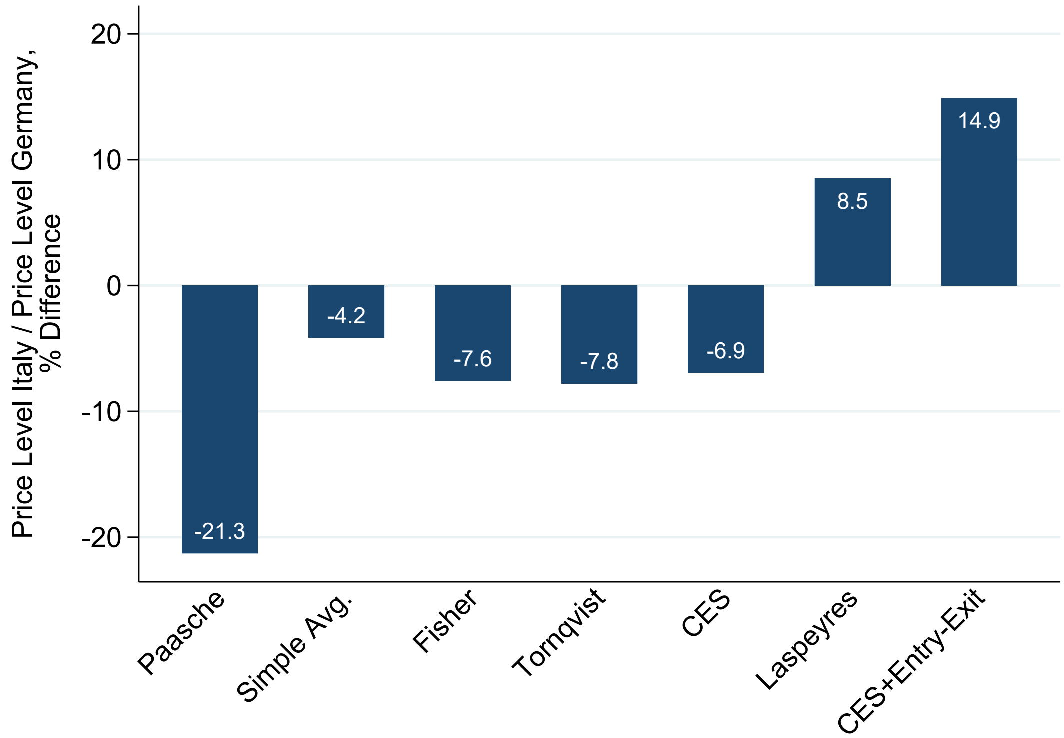
(n) Poland



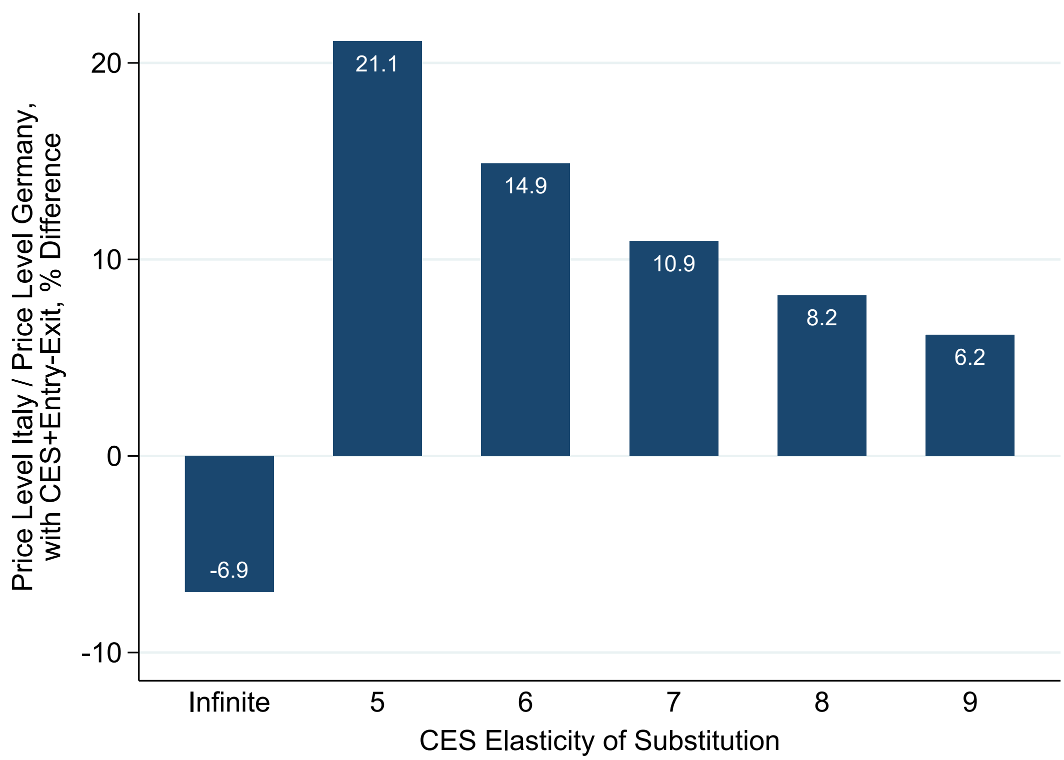
(o) Sweden

Notes: This figure reports inflation inequality on continued products for the 13 largest economies in our sample where socio-demographic information are available.

Figure 7: PPP between Italy and Germany in 2016, barcode match



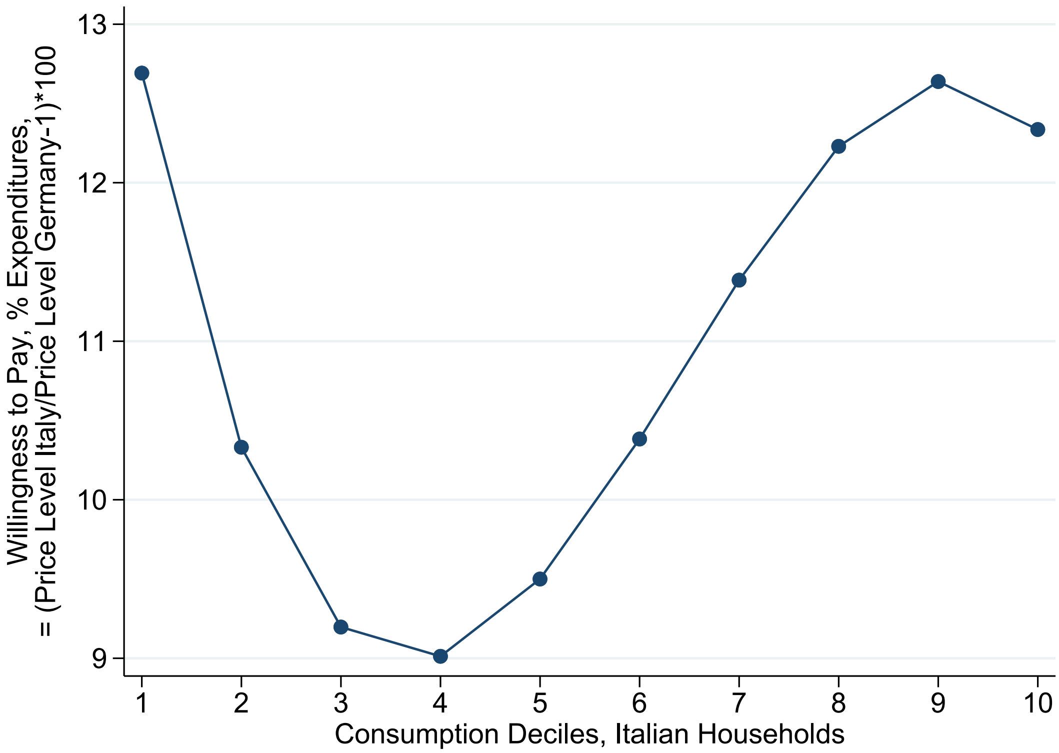
(a) Main results



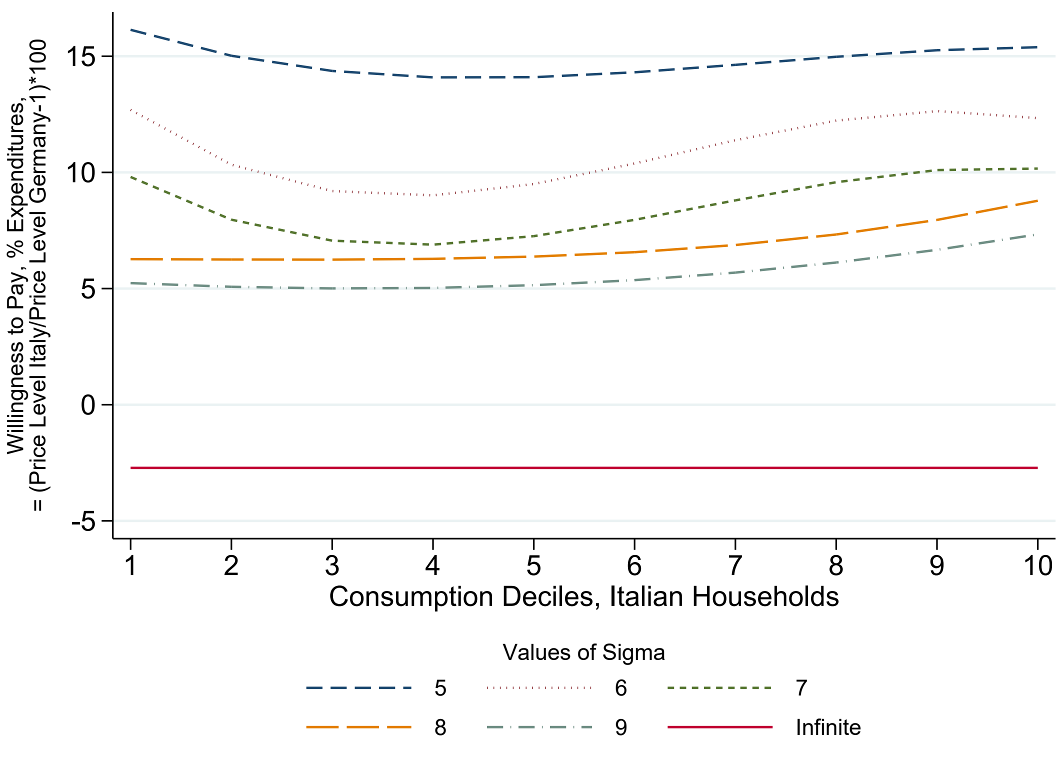
(b) CES with entry-exit, sensitivity

Notes: This figure reports PPP estimates for Italy relative to Germany across different specifications. Products are matched by identical barcodes.

Figure 8: Non-homothetic PPP in between Italy and Germany in 2016, barcode match



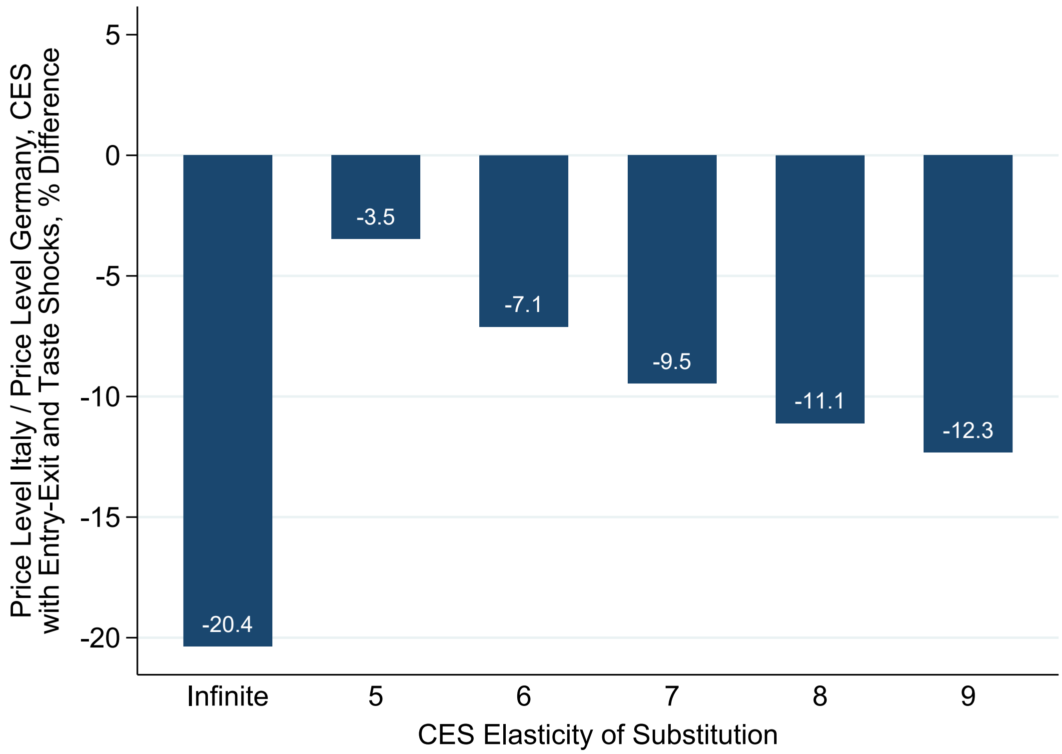
(a) Main results



(b) Sensitivity Analysis

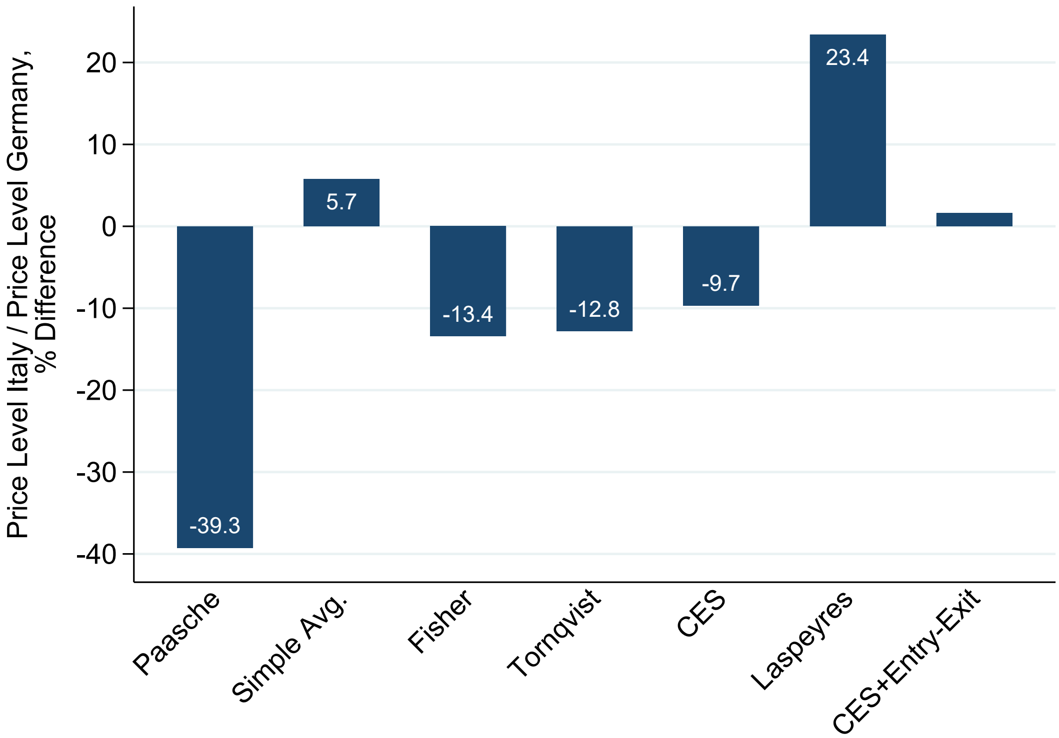
Notes: This figure reports nhPPP estimates for Italy relative to Germany using different values for σ. Products are matched by identical barcodes.

Figure 9: PPP in between Italy and Germany in 2016 with taste shocks, barcode match

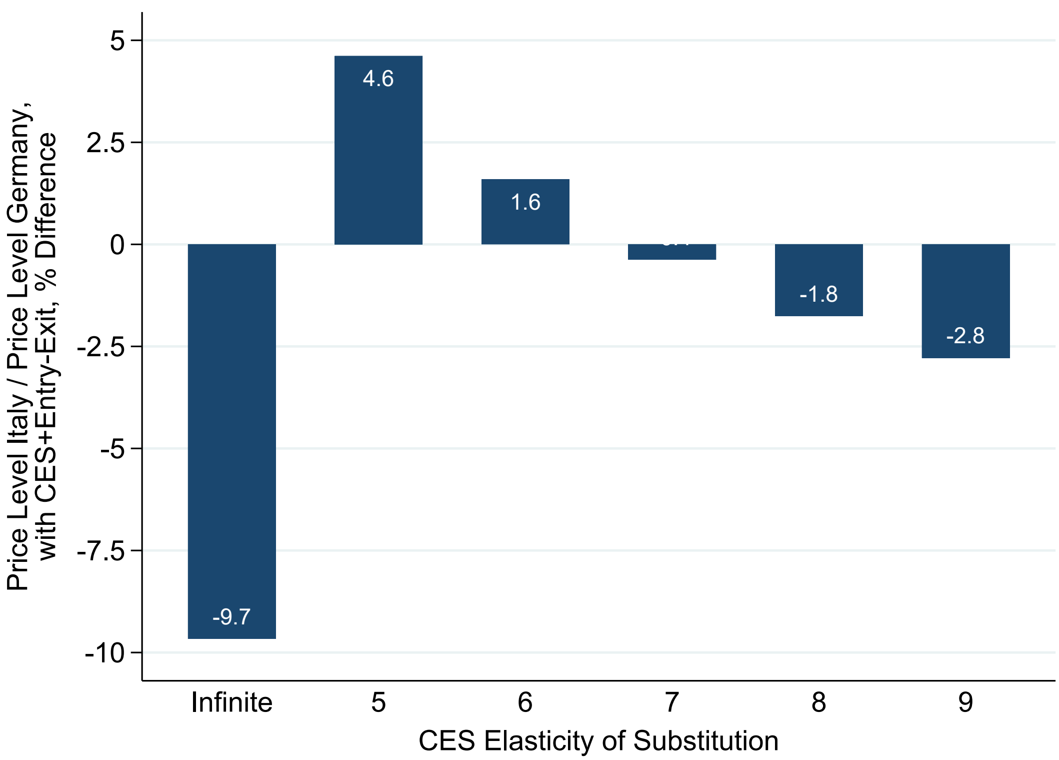


Notes: This figure reports PPP estimates for Italy relative to Germany across different specifications, allowing for taste shocks. Products are matched by identical barcodes.

Figure 10: PPP between Italy and Germany in 2016, manufacturer match



(a) Main results

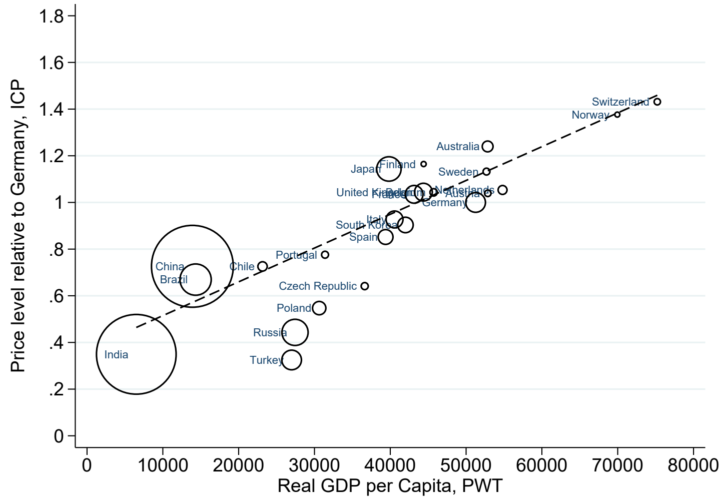


(b) CES with entry-exit, sensitivity

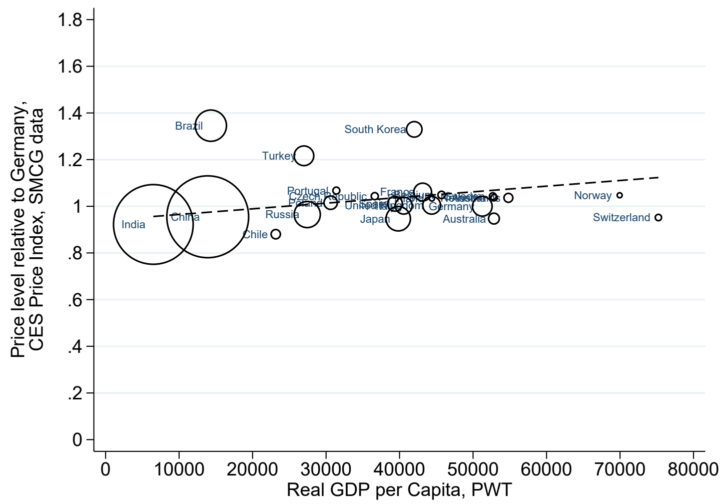
Notes: This figure reports PPP estimates for Italy relative to Germany across different specifications. Products are matched by manufacturers.

Figure 11: Cross-country Relationships between PPP Adjustment and Real GDP, SMCG sample

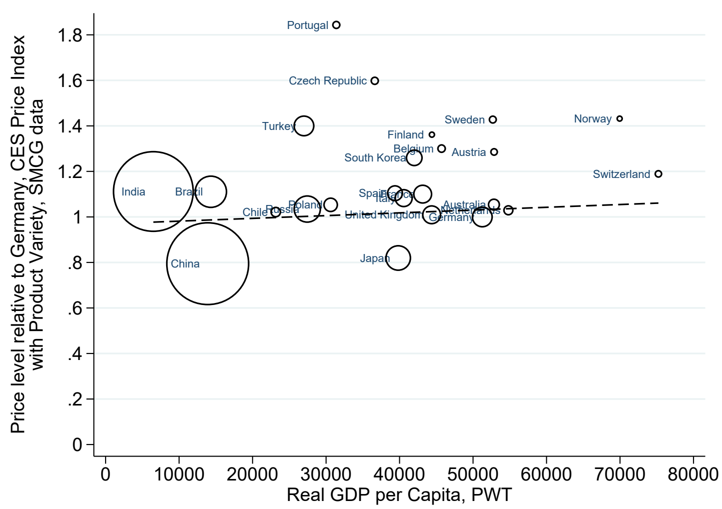
Panel A: With ICP price index



Panel B: With CES price index for identical barcodes



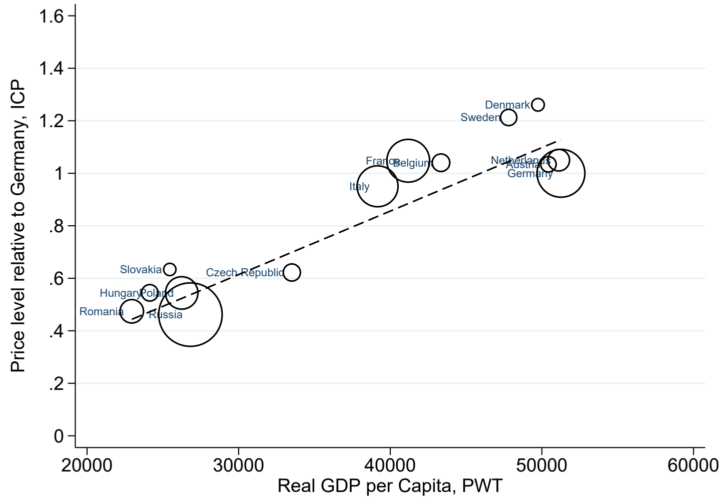
Panel C: With CES price index for identical barcodes and product variety adjustment



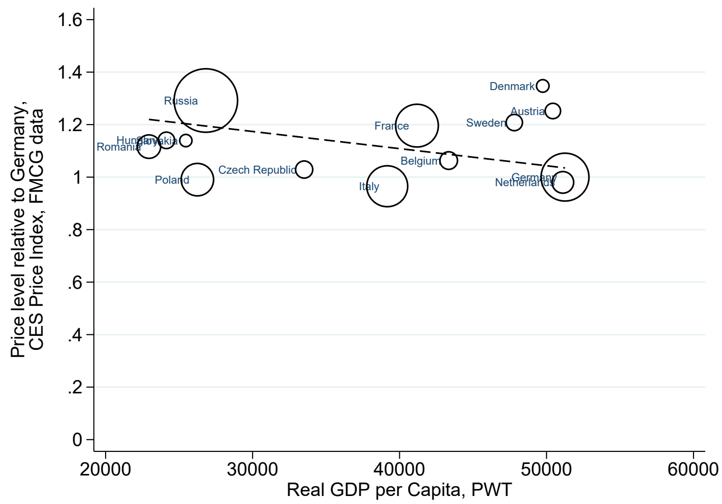
Notes: All panels of this figure uses the sample of 24 SMCG countries for which a match across identical barcodes could be implemented in 2017.

Figure 12: Cross-country Relationships between PPP Adjustment and Real GDP, SMCG sample

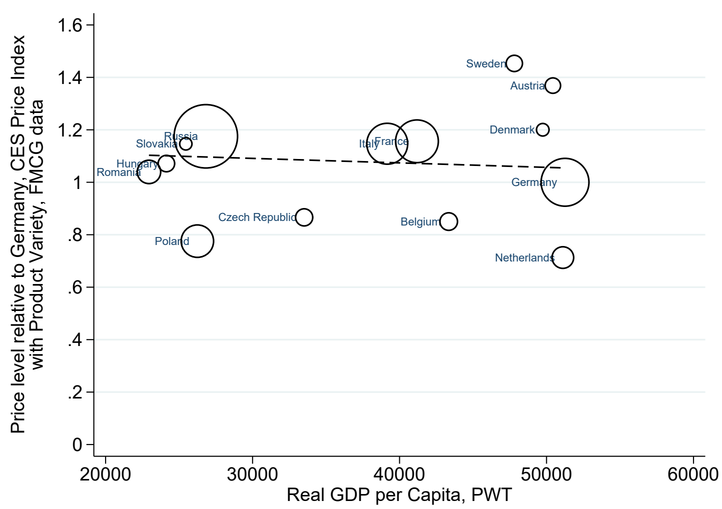
Panel A: With ICP price index



Panel B: With CES price index for identical barcodes



Panel C: With CES price index for identical barcodes and product variety adjustment



Notes: All panels of this figure uses the sample of 24 SMCG countries for which a match across identical barcodes could be implemented in 2017.

Online Appendix to “Prices and Global Inequality: New Evidence from Worldwide Scanner Data”

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A Background information about our global scanner price data set[2]

A.1 Data coverage and sources

The aim of marketing companies to run (very costly) panels is to provide insights into the dynamics of sales of products and the purchasing behavior of households to their clients. In the field of fast-moving consumer goods (FMCG), there exist two major types of panels: retailer and household panels. Members of the former are retailers which transmit the sales data of their branches to the contracted marketing companies at a regular (mostly weekly) frequency. The collected data in particular comprise volumes of products sold and their prices. They are especially well suited to analyze question concerning the relative market share of a product and the sales' locations. Household panels are made of households recording their purchases on a continuous base. These panels provide information not only about the quantity of products bought and the price paid but also the (socio-economic) characteristics of the buyers. Our study makes use of this type of data.

With the exception of the U.S., the data we are employing originally stem from the two marketing companies GfK and Kantar.[3] Concerning their household panel business, these two companies cooperate which, e.g., implies that they do not run parallel household panels in any of the 34 countries for which we have data. To be able to provide analyses on a global scale to their customers, the two companies founded the joint venture Europanel. Here, data from the two institutes are harmonized to create customer-specific, international reports. Lagged data (by one year) are in turn provided to AiMark which is a non-profit foundation, promoting research in the area of marketing and macroeconomics (the latter via its "Miggroprices" initiative).

The data collected cover purchases of so-called fast-moving consumer goods (FMCG, also denoted as consumer-packaged goods), i.e., products that are purchased and consumed frequently by households and that are characterized by relatively low prices. Goods generally fall into the categories food and beverages and personal and household care.

[2]The presentation in this Section heavily rests on Guenther, Vossebein, and Wildner (2019). This book (which is unfortunately only available in German) contains a very comprehensive and insightful exposition of all aspects relevant for panel research in the area of marketing. A particular emphasis is given to GfK-run panels in this book. A very good discussion of a Kantar-run panel is available (as of March 2020) at: https://www.ukessays.com/essays/marketing/kantar-worldpanel-research-method-and-the-competitive-environment-marketing-essay.php

[3]The data for the U.S. are provided by IRI.

A.2 Panel design and sample construction

Since the objective of household panels is to provide meaningful insights into the shopping behavior of the entirety of s country's households, their population is defined as the set of all private households (with permanent residence) in that country. This definition implies that purchases of FMCG by institutions such as canteens, offices, restaurants or by non-permanent residents such as tourists are not captured by household panels.

The panel samples are constructed to be representative in the sense that results obtained from the sample can be generalized to the overall population. To draw households from the population, quota sampling rather than random sampling is applied. There are two major reasons for doing so: First, there is a lock of ready-made lists of all existing households from which to sample randomly. Secondly, the intended long-run nature of the cooperation between the marketing company and panel members requires a strong commitment on the site of the latter. As a consequence, rejection rates of addressed potential new panel members are generally very high implying that random sampling methods would almost certainly fail to deliver representative samples.

The quota sampling approach chosen typically follows a multi-stage procedure. To achieve representativeness (in the above mentioned sense), households are selected such that their demographic profile matches that of the country's overall population. The first step in creating the sample is to define subgroups of households based on demographic characteristics. To determine the reference values for these subgroups, usually data from national statistical offices are employed. These data are updated regularly (where the updating frequency is generally annual). Characteristics used to define the relative sizes of subgroups include information on the household size, social class, age (of the household's main shopper), number of children under a certain age, and place of residence.

The set of the latter is determined according to the following process: First, the country is split into regional units (often called "sample points"). These units can either be homogeneous (such as in the UK) or stratified (e.g., based on state and location size such as in Germany) entities. In the case of stratified entities, a proportional, stratified sample of regional unit is drawn as a next step. Households are then recruited (in a non-random manner) in the (selected) sample points based on the quota criteria. In doing so, it is made sure that the proportion of demographic characteristics in the region corresponds to that in the population.

This principle is generally applied to all household segments, exceptions are made only in very rare cases. One such exception might be that the proportion of single-person households in the sample is smaller than that in the population. If this applies, it is done for two reasons: First, single-person households tend to shop significantly less in the relevant product groups. Second, the recruiting process and maintenance efforts are particularly challenging - and thus costly - for young single-person households. To correct for potential biases associated with non-proportional shares of segments, weighting factors are computed and applied. The calculation of these factors is generally done using iterative proportional fitting (raking).

A.3 Data collection and processing

The major method for recording the data depends on the structure of a country's market (which is closely linked to the development stage of its economy). For the FMCG market, historically (until the 1990s), purchases were recorded in written form in the context of a "household calendar", where every week a report sheet was torn off, filled in with the purchases made and sent back to the marketing research institute.

Nowadays, where products are typically equipped with barcodes, three major recording methods are available: the POS (point-of-sales) scanning, in-home scanning, respectively electronic diary, and data acquisition via the internet. A forth alternative is the combination of scanning and data recording via the internet in the context of the so-called "Scan-It" procedure.[4] Concerning the method chosen by the marketing company, it typically applies two criteria: First, the method must be technically feasible and sensible in the respectively given market context. Second, it should minimize the efforts for the panelists (to accomplish high levels of panel continuity).

After the purchase data have been transferred to the marketing company, a comprehensive structured checking process is undertaken. The form of the checking process strongly depends on the data collection method but typically comprises the dimension "purchase" and "household". If the good indicated in a transaction is already listed in the company's barcode dictionary, the checking process primarily focusses on the plausibility of the quantity and price reported. For articles not listed in the barcode dictionary yet, the first step is to obtain more information about the

[4] In the context of the POS scanning procedure, panelists get a form of ID card that they present at cash desks of retail outlets where they shop. The sales of the household are then automatically recorded and transferred to the marketing company. This method requires a contractual relationship between the marketing company and the retailer. In the context of in-home scanning (respectively electronic diary), households register their purchases at home via a scanning device. When doing so, they type in additional information on the purchase made such as the price paid and the retailer at which they bought it. When data is transferred via the internet, the household logs on at a specified website and types in the purchase information employing web forms provided by the marketing company.. Currently, another process is being prepared, namely the so-called till-roll scanning.

underlying product. This process starts with extracting the information contained in the GTIN and is - depending on the circumstances prevailing for a given good - complemented with contacting the manufacturer, the company's field service and/or the household having purchased the good.

The second dimension of checks concerns the quality of the cooperation of panelists. These checks comprise several aspects. First, it is examined whether a given household has provided any report at all. One reason for doing so is, that usually only transactions from those households are included in the final reporting that have reported for a minimum number of weeks. Moreover, this information is used as an indicator for the level of cooperation motivation of a given household. A second check analyzes whether the purchase quantities reported by a household over a longer time horizon are plausible. As a benchmark, the purchasing behavior of households with the same socio-demographic structure are used. Additionally, the dynamics of the household's purchases are considered. Should the analysis of a household's behavior indicate a declining quality of cooperation activity, it is contacted and asked to improve its recording behavior. Should these efforts not be successful, the cooperation is terminated.

A.4 Potential data issues and specifities for emerging-market economies

A.4.1 Potential data issues

As stated above, the objective of running a household panel is to provide analyses of household-specific purchasing patterns that can be extended to the overall household population of a country. This requires that the sample of households constructed is representative. Subsection A.2 already mentioned that specific household segments might on purpose be under- (or over-) represented in some countries. A difficulty that is common across countries consists of properly representing both the lowest and highest social classes of a society. This is particularly problematic for the representation of product groups in the sample that are primarily consumed by one of the mis-represented population segments (such as champagne or expensive perfumes by upper social classes).

The generalization of sample outcomes might also be harmed by other factors giving rise to selection bias and by panel conditioning. A Gfk-internal study (by Sylvia Pethold and quoted in Guenther, Vossebein, and Wildner, 2019) indeed shows that these phenomena play a role. Comparing the behavior of panelists with those from households randomly selected shows that

- Panel households have a somewhat larger tendency to inform themselves more intensively about products supplied.[5]
- Panel households are somewhat less brand-oriented.[6]
- Panel households are somewhat more price-conscious than the average of the population (70.5% vs. 68.6%).
- Panel households tend to be more innovative.[7]
- Panel households shop more consciously.[8]

On the other hand, panel conditioning does not seem to play a major role: Monitoring household behavior over time reveals that the reporting behavior does not show any further adaptions as soon as a stable cooperation relationship has been established.

A third major data-related issue results from the fact that household panels primarily record the transactions made by the person being generally in charge for the household shopping purchases (in the further denoted as the "household main shopper"). While panel institutes request that also the purchases (in the relevant product groups) by other household members are recorded, this is usually only partly the case in practice. This fact can impact the records of product groups that household members primarily buy for themselves. Examples are cosmetic articles, shampoo, cigarettes and certain sweets such as chewing gum or individual candy bars. On the other hand, the under-representation of these types of goods should not have a major influence on the inflation a given household experiences and thus on our results.

The last data comment concerns unpackaged goods (such as fresh fruit, meat and sausage products) and goods from discounters not participating in the GS1 system (Aldi). Both groups of goods have in common that they do not have a barcode in the form a GTIN. For those countries for which unpackaged goods are included in our purchase data, they were assigned a (unique) product code by GfK/Kantar. The

[5] This statement is derived from the two following observations: 79% of the panel households but only 65% of the random sample obtain regular information about product offers. 16% of the members of the random sample but only 11% of the panel households have a sticker on their mailbox prohibiting the insertion of advertising.

[6] This statement is derived from the observation that 26% of the members of the random sample but only 12% of the panel households supported the statement that branded articles are better than products with unknown names.

[7] This statement is derived from the observation that the statement “I like trying out new products” is approved by 57% of panel households, but only 48% of the population.

[8] This statement is derived from the observation that 84% of panel households write a shopping list before shopping, but only 68% of the random-sample households.

same is true for discounter goods without a GTIN (where these goods are included in all countries).

A.4.2 Specifities of emerging market economies

Generally, the panel design in emerging market economies has the same objectives and follows the same principles as that for advanced economies. Moreover, articles are generally equipped with barcodes such that the data collection process is also comparable.

A.5 Major panel facts

References

Guenther, Martin, Ulrich Vossebein, and Raimund Wildner (2019). *Marktforschung mit Panels (Markt research with panels)*. 3rd edition. Wiesbaden: Springer Wiesbaden. ISBN: 9783658086480.

Appendix Table A1: Year-on-year Inflation for Continued Products, All Countries

Country	Year	Tornqvist	CES	Laspeyres	Paasche	Fisher	GPaasche	GLaspeyres	Walsh	ME
Argentina	2012	1.172	1.173	1.195	1.149	1.172	1.178	1.166	1.174	1.172
Argentina	2013	1.206	1.207	1.25	1.163	1.205	1.209	1.203	1.208	1.208
Argentina	2014	1.353	1.355	1.402	1.308	1.354	1.352	1.354	1.356	1.354
Argentina	2015	1.196	1.196	1.233	1.162	1.197	1.198	1.195	1.196	1.198
Argentina	2016	1.323	1.325	1.359	1.288	1.323	1.33	1.316	1.325	1.326
Argentina	2017	1.22	1.221	1.254	1.187	1.22	1.223	1.218	1.222	1.217
Argentina	2018	1.283	1.283	1.318	1.25	1.283	1.289	1.277	1.283	1.283
Austria	2009	1.001	1.001	1.005	.997	1.001	1.004	.998	1.001	1.001
Austria	2010	.991	.991	.994	.989	.991	.995	.988	.991	.991
Austria	2011	1.031	1.031	1.034	1.027	1.031	1.035	1.027	1.032	1.031
Austria	2012	1.022	1.022	1.025	1.019	1.022	1.025	1.019	1.022	1.022
Austria	2013	1.015	1.015	1.017	1.012	1.015	1.018	1.011	1.015	1.015
Austria	2014	1.014	1.015	1.017	1.012	1.014	1.018	1.011	1.015	1.014
Austria	2015	1.007	1.007	1.009	1.005	1.007	1.011	1.003	1.007	1.007
Austria	2016	.998	.998	1	.996	.998	1.002	.994	.998	.998
Austria	2017	1.01	1.01	1.012	1.008	1.01	1.015	1.005	1.011	1.01
Austria	2018	1.008	1.008	1.01	1.006	1.008	1.012	1.004	1.008	1.008
Belgium	2009	1.01	1.01	1.012	1.007	1.01	1.016	1.004	1.009	1.01
Belgium	2010	1.005	1.006	1.008	1.003	1.006	1.012	.998	1.006	1.006
Belgium	2011	1.016	1.016	1.019	1.014	1.016	1.023	1.009	1.017	1.016
Belgium	2012	1.022	1.023	1.025	1.02	1.023	1.028	1.016	1.023	1.023
Belgium	2013	1.025	1.025	1.028	1.022	1.025	1.03	1.02	1.025	1.025
Belgium	2014	.998	.998	1.001	.995	.998	1.003	.993	.998	.998
Belgium	2015	1.003	1.003	1.005	1	1.003	1.008	.997	1.003	1.003
Belgium	2016	1.016	1.015	1.019	1.013	1.016	1.02	1.011	1.015	1.016
Belgium	2017	1.009	1.009	1.012	1.006	1.009	1.013	1.005	1.009	1.009
Belgium	2018	1.017	1.017	1.021	1.014	1.018	1.021	1.013	1.018	1.018
Bolivia	2013	1.036	1.036	1.043	1.029	1.036	1.038	1.033	1.036	1.036
Bolivia	2014	.973	.973	.99	.953	.971	.973	.973	.973	.971
Bolivia	2015	1.02	1.021	1.029	1.013	1.021	1.028	1.012	1.021	1.02
Bolivia	2016	1.033	1.034	1.041	1.018	1.03	1.047	1.019	1.034	1.03
Bolivia	2017	.998	.999	1.012	.988	1	1.006	.991	.998	1
Bolivia	2018	1.015	1.015	1.021	1.009	1.015	1.024	1.006	1.015	1.015
Brazil	2014	1.057	1.059	1.069	1.036	1.052	1.077	1.037	1.054	1.051
Brazil	2015	1.054	1.055	1.065	1.031	1.048	1.065	1.044	1.05	1.048
Brazil	2016	1.055	1.059	1.069	1.033	1.051	1.085	1.026	1.054	1.051
Brazil	2017	1.017	1.019	1.032	.997	1.014	1.032	1.003	1.015	1.014
Brazil	2018	1.009	1.011	1.021	.99	1.005	1.024	.995	1.007	1.007
Central America	2013	.959	.989	1.027	.945	.985	1.176	.784	.987	.983
Central America	2014	.971	.999	1.013	.975	.994	1.14	.827	.997	.995
Central America	2015	.99	1.011	1.028	.99	1.009	1.149	.854	1.011	1.007
Central America	2016	.958	.964	.987	.943	.965	1.138	.808	.962	.964
Central America	2017	1.001	1.014	1.028	.986	1.007	1.178	.852	1.012	1.007
Central America	2018	.933	.966	.991	.947	.969	1.125	.773	.967	.969
Chile	2013	1.028	1.029	1.036	1.015	1.025	1.032	1.024	1.026	1.025
Chile	2014	1.023	1.023	1.031	1.009	1.02	1.027	1.018	1.021	1.019
Chile	2015	1.015	1.015	1.021	1.005	1.013	1.018	1.012	1.013	1.013

Country	Year	Tornqvist	CES	Laspeyres	Paasche	Fisher	GPaasche	GLaspeyres	Walsh	ME
Chile	2016	1.068	1.068	1.076	1.056	1.066	1.075	1.06	1.066	1.066
China	2012	1.026	1.026	1.029	1.024	1.026	1.028	1.024	1.027	1.026
China	2013	1.01	1.01	1.012	1.007	1.01	1.012	1.007	1.01	1.01
China	2014	1.009	1.009	1.012	1.005	1.009	1.011	1.006	1.009	1.009
China	2015	1	1	1.004	.996	1	1.002	.997	1	1
China	2016	.993	.993	.996	.989	.992	.997	.988	.993	.992
China	2017	1.004	1.004	1.006	1.001	1.004	1.008	.999	1.004	1.004
China	2018	1.011	1.011	1.014	1.007	1.01	1.016	1.006	1.011	1.011
Colombia	2013	1.004	1.005	1.007	.988	.998	1.014	.995	.999	.998
Colombia	2014	.996	.997	.999	.981	.99	1.006	.986	.99	.99
Colombia	2015	1.015	1.015	1.02	.995	1.007	1.033	.998	1.009	1.007
Colombia	2016	1.054	1.057	1.067	1.029	1.048	1.084	1.025	1.049	1.048
Colombia	2017	1.027	1.028	1.03	1.005	1.018	1.046	1.009	1.02	1.018
Colombia	2018	1.011	1.01	1.019	.988	1.003	1.022	1	1.003	1.004
Czech Republic	2014	1.008	1.01	1.018	1	1.009	1.01	1.006	1.01	1.009
Czech Republic	2015	.981	.981	.988	.975	.982	.987	.976	.981	.982
Czech Republic	2016	.984	.984	.989	.98	.984	.991	.978	.984	.985
Czech Republic	2017	1.043	1.044	1.049	1.038	1.043	1.051	1.035	1.044	1.043
Czech Republic	2018	1.008	1.008	1.014	1.002	1.008	1.014	1.002	1.008	1.008
Germany	2006	1.014	1.015	1.017	1.011	1.014	1.017	1.011	1.016	1.013
Germany	2007	1.015	1.015	1.017	1.012	1.014	1.017	1.012	1.015	1.014
Germany	2008	1.039	1.039	1.042	1.036	1.039	1.042	1.036	1.04	1.039
Germany	2009	.986	.986	.989	.984	.986	.989	.983	.986	.986
Germany	2010	.997	.997	.999	.996	.997	1	.995	.997	.997
Germany	2011	1.018	1.019	1.02	1.017	1.018	1.021	1.016	1.019	1.019
Germany	2012	1.016	1.016	1.018	1.015	1.016	1.019	1.013	1.016	1.016
Germany	2013	1.018	1.019	1.02	1.017	1.018	1.02	1.016	1.019	1.018
Germany	2014	.997	.997	.999	.996	.997	.999	.996	.998	.998
Germany	2015	1	1	1.001	.998	1	1.002	.997	1	1
Germany	2016	.999	.999	1	.997	.999	1	.997	.999	.999
Germany	2017	1.015	1.015	1.017	1.012	1.014	1.017	1.013	1.014	1.014
Germany	2018	1.013	1.013	1.015	1.01	1.013	1.014	1.012	1.013	1.013
Denmark	2014	.99	.991	1.002	.98	.991	.993	.987	.991	.991
Denmark	2015	1.001	1.001	1.009	.994	1.002	1.005	.997	1.001	1.001
Denmark	2016	.993	.993	.999	.986	.993	.998	.987	.993	.993
Denmark	2017	.986	.987	.99	.982	.986	.99	.983	.987	.986
Denmark	2018	1.024	1.025	1.028	1.021	1.025	1.03	1.019	1.025	1.025
Ecuador	2013	1.032	1.032	1.04	1.014	1.027	1.038	1.026	1.028	1.025
Ecuador	2014	1.012	1.013	1.021	.994	1.007	1.017	1.007	1.008	1.007
Ecuador	2015	.952	.952	.962	.929	.945	.958	.946	.948	.946
Ecuador	2016	1.004	1.004	1.009	.98	.995	1.029	.979	.996	.995
Ecuador	2017	1.01	1.01	1.022	.987	1.005	1.023	.997	1.004	1.004
Ecuador	2018	.996	.998	1.001	.979	.99	1.01	.982	.992	.99
Spain	2009	.981	.981	.984	.979	.982	.987	.976	.981	.981
Spain	2010	.993	.993	.995	.991	.993	.998	.988	.993	.993
Spain	2011	1.012	1.012	1.014	1.01	1.012	1.017	1.007	1.012	1.012
Spain	2012	1.003	1.003	1.004	1.002	1.003	1.008	.998	1.003	1.003
Spain	2013	1.016	1.016	1.018	1.015	1.016	1.021	1.011	1.016	1.016

Country	Year	Tornqvist	CES	Laspeyres	Paasche	Fisher	GPaasche	GLaspeyres	Walsh	ME
Spain	2014	.991	.991	.993	.989	.991	.995	.987	.991	.991
Spain	2015	1.007	1.007	1.008	1.006	1.007	1.014	1.001	1.008	1.007
Spain	2016	.998	.999	.999	.998	.998	1.005	.991	.999	.998
Spain	2017	1.008	1.008	1.01	1.007	1.008	1.014	1.002	1.008	1.008
Spain	2018	.996	.997	.999	.993	.996	1.003	.988	.998	.997
France	2009	.996	.996	.998	.994	.996	.997	.994	.995	.996
France	2010	.994	.994	.996	.993	.994	.995	.994	.994	.995
France	2011	1.014	1.014	1.015	1.012	1.014	1.015	1.012	1.014	1.014
France	2012	1.008	1.008	1.01	1.006	1.008	1.009	1.007	1.008	1.008
France	2013	1.001	1.001	1.003	1	1.002	1.003	1	1.001	1.002
France	2014	.987	.987	.989	.985	.987	.988	.986	.987	.987
France	2015	.984	.984	.986	.982	.984	.985	.983	.984	.984
France	2016	.987	.987	.989	.985	.987	.988	.986	.987	.987
France	2017	.996	.996	.998	.995	.996	.998	.995	.996	.996
France	2018	1.003	1.003	1.005	1.002	1.003	1.005	1.002	1.003	1.004
Hungary	2011	1.053	1.054	1.056	1.05	1.053	1.061	1.045	1.054	1.053
Hungary	2012	1.064	1.065	1.071	1.057	1.064	1.069	1.06	1.065	1.064
Hungary	2013	1.022	1.021	1.027	1.017	1.022	1.028	1.015	1.021	1.022
Hungary	2014	1	1	1.004	.996	1	1.005	.995	1	1
Hungary	2015	1.003	.999	1	1.002	1.001	1.016	.991	.998	1.001
Hungary	2016	1.004	1.003	1.007	1	1.004	1.007	1.001	1.003	1.003
Hungary	2017	1.037	1.038	1.042	1.032	1.037	1.04	1.035	1.038	1.037
Hungary	2018	1.036	1.036	1.04	1.033	1.036	1.04	1.032	1.037	1.036
Ireland	2014	1.001	1.001	1.006	.996	1.001	1.007	.994	1.001	1.001
Ireland	2015	.99	.99	.994	.985	.99	.994	.985	.99	.989
Ireland	2016	.996	.994	.999	.992	.995	1.003	.989	.994	.995
Ireland	2017	.987	.987	.991	.983	.987	.992	.982	.987	.987
Ireland	2018	.986	.986	.991	.982	.986	.992	.981	.986	.986
India	2013	.992	.992	.993	.991	.992	.994	.99	.992	.992
India	2014	1.002	1.002	1.003	1.001	1.002	1.003	1.001	1.001	1.002
India	2015	1.008	1.008	1.009	1.007	1.008	1.009	1.007	1.008	1.008
India	2016	1.013	1.014	1.014	1.013	1.014	1.016	1.011	1.014	1.014
Italy	2013	.967	.968	.965	.967	.967	.972	.962	.967	.967
Italy	2014	.99	.992	.988	.99	.99	1.006	.975	.99	.99
Italy	2015	1.017	1.015	1.019	1.018	1.017	1.029	1.007	1.016	1.017
Italy	2016	.997	.999	.996	.998	.997	1.004	.991	.997	.997
Italy	2017	1.002	1.003	1.001	1.002	1.002	1.01	.995	1.002	1.002
Italy	2018	.994	.996	.993	.995	.994	1.003	.986	.994	.994
Netherlands	2009	.996	.996	1	.993	.996	.999	.994	.996	.996
Netherlands	2010	.995	.996	.998	.993	.996	1	.991	.996	.996
Netherlands	2011	1.015	1.015	1.017	1.012	1.015	1.02	1.009	1.016	1.015
Netherlands	2012	1.013	1.013	1.016	1.01	1.013	1.018	1.007	1.013	1.013
Netherlands	2013	1.015	1.015	1.019	1.011	1.015	1.019	1.01	1.015	1.015
Netherlands	2014	.999	.999	1.003	.996	.999	1.005	.994	.999	1
Netherlands	2015	.995	.995	.999	.991	.995	.999	.991	.995	.995
Netherlands	2016	1.001	1.001	1.005	.997	1.001	1.005	.996	1.001	1.001
Netherlands	2017	1.015	1.016	1.021	1.011	1.016	1.02	1.01	1.017	1.016
Netherlands	2018	1.013	1.014	1.017	1.01	1.013	1.019	1.008	1.014	1.013

Country	Year	Tornqvist	CES	Laspeyres	Paasche	Fisher	GPaasche	GLaspeyres	Walsh	ME
Peru	2013	1.03	1.029	1.039	1.012	1.025	1.033	1.027	1.025	1.026
Peru	2014	1.02	1.022	1.024	1.01	1.017	1.032	1.008	1.02	1.017
Peru	2015	.992	.993	1.004	.974	.989	.998	.986	.99	.99
Peru	2016	1.019	1.019	1.026	1.001	1.013	1.027	1.01	1.015	1.014
Peru	2017	1.003	1.004	1.015	.982	.999	1.008	.999	1	.999
Poland	2012	1.028	1.027	1.033	1.023	1.028	1.03	1.025	1.027	1.028
Poland	2013	.997	.997	1	.994	.997	1	.994	.997	.996
Poland	2014	1.009	1.009	1.012	1.006	1.009	1.013	1.006	1.009	1.009
Poland	2015	.975	.974	.977	.972	.975	.978	.972	.974	.975
Poland	2016	.998	1	.999	.999	.999	1.003	.992	1.001	.999
Poland	2017	1.026	1.026	1.028	1.024	1.026	1.029	1.023	1.026	1.026
Portugal	2011	1.014	1.014	1.017	1.012	1.014	1.026	1.003	1.014	1.014
Portugal	2012	1.023	1.024	1.028	1.02	1.024	1.033	1.014	1.024	1.024
Portugal	2013	.998	.998	1.001	.995	.998	1.008	.989	.998	.998
Portugal	2014	.976	.976	.978	.973	.976	.986	.966	.976	.976
Portugal	2015	1.004	1.004	1.006	1.001	1.004	1.015	.993	1.004	1.004
Portugal	2016	.985	.984	1.077	.915	.993	1.003	.966	.986	.998
Portugal	2017	1.026	1.027	1.032	1.021	1.027	1.035	1.018	1.027	1.027
Portugal	2018	.963	.964	.972	.954	.963	.969	.958	.965	.962
Romania	2014	.967	.968	.979	.956	.967	.972	.962	.969	.967
Romania	2015	.931	.933	.935	.931	.933	.944	.919	.933	.932
Romania	2016	1.015	1.015	1.019	1.011	1.015	1.023	1.007	1.015	1.016
Romania	2017	1.018	1.019	1.021	1.015	1.018	1.026	1.01	1.019	1.018
Romania	2018	1.027	1.028	1.03	1.025	1.028	1.036	1.018	1.028	1.027
Russia	2015	1.166	1.167	1.172	1.162	1.167	1.175	1.157	1.167	1.167
Russia	2016	1.053	1.055	1.056	1.053	1.054	1.063	1.044	1.056	1.054
Russia	2017	1.006	1.006	1.012	1	1.006	1.01	1.001	1.006	1.006
Russia	2018	.999	.999	1.005	.993	.999	1.001	.997	.999	.999
South Africa	2015	1.06	1.06	1.062	1.057	1.06	1.066	1.054	1.06	1.06
Sweden	2007	1.005	1.005	1.008	1.003	1.005	1.008	1.002	1.006	1.005
Sweden	2008	1.059	1.059	1.062	1.056	1.059	1.063	1.054	1.059	1.059
Sweden	2009	1.023	1.023	1.027	1.019	1.023	1.026	1.02	1.024	1.023
Sweden	2010	.995	.995	.999	.992	.996	.998	.993	.995	.996
Sweden	2011	1.014	1.014	1.018	1.01	1.014	1.018	1.01	1.014	1.014
Sweden	2012	1.005	1.005	1.009	1.001	1.005	1.008	1.002	1.005	1.005
Sweden	2013	1.004	1.004	1.008	1.001	1.004	1.009	1	1.004	1.004
Sweden	2014	.997	.997	1	.995	.997	1.002	.993	.997	.997
Sweden	2015	1.001	1.001	1.005	.998	1.001	1.005	.997	1.001	1.001
Sweden	2016	.993	.993	.996	.99	.993	.997	.989	.993	.993
Sweden	2017	1.025	1.026	1.03	1.021	1.026	1.03	1.021	1.026	1.026
Sweden	2018	1.015	1.015	1.018	1.012	1.015	1.019	1.01	1.015	1.015
Slovakia	2014	.987	.988	.996	.978	.987	.991	.983	.989	.987
Slovakia	2015	.981	.981	.985	.976	.981	.989	.973	.981	.981
Slovakia	2016	.979	.979	.983	.975	.979	.983	.975	.979	.979
Slovakia	2017	1.032	1.032	1.037	1.027	1.032	1.038	1.026	1.033	1.032
Slovakia	2018	1.018	1.018	1.023	1.012	1.017	1.024	1.011	1.018	1.018
Thailand	2014	1.007	1.007	1.01	1.004	1.007	1.007	1.007	1.007	1.007

Country	Year	Tornqvist	CES	Laspeyres	Paasche	Fisher	GPaasche	GLaspeyres	Walsh	ME
Thailand	2015	.996	.997	1	.993	.997	.997	.996	.997	.997
Thailand	2016	.995	.995	.998	.992	.995	.996	.994	.995	.995
Thailand	2017	.996	.996	.999	.993	.996	.997	.995	.996	.996
Thailand	2018	1.005	1.005	1.009	1.002	1.005	1.005	1.005	1.005	1.005
Turkey	2014	1.086	1.086	1.087	1.084	1.086	1.086	1.085	1.086	1.085
Turkey	2015	1.065	1.065	1.068	1.064	1.066	1.066	1.064	1.064	1.066
Turkey	2016	1.075	1.075	1.077	1.072	1.074	1.078	1.072	1.075	1.075
Taiwan	2014	1.002	1.002	1.011	.993	1.002	1.005	.998	1.002	1.002
Taiwan	2015	.999	.999	1.004	.993	.999	1.006	.993	.999	.997
Taiwan	2016	.998	.998	1.006	.99	.998	1.004	.991	.998	.997
Taiwan	2017	1.006	1.007	1.015	.998	1.006	1.013	1	1.007	1.006
Taiwan	2018	1.018	1.018	1.03	1.008	1.019	1.024	1.012	1.019	1.019
United Kingdom	2007	1.016	1.016	1.023	1.008	1.016	1.014	1.017	1.016	1.015
United Kingdom	2008	1.055	1.056	1.063	1.047	1.055	1.056	1.054	1.056	1.055
United Kingdom	2009	1.037	1.037	1.048	1.026	1.037	1.034	1.039	1.038	1.037
United Kingdom	2010	1.001	1.002	1.01	.993	1.001	1	1.003	1.002	1.001
United Kingdom	2011	1.033	1.033	1.041	1.025	1.033	1.031	1.034	1.033	1.033
United Kingdom	2012	1.024	1.025	1.033	1.016	1.025	1.022	1.026	1.025	1.024
United Kingdom	2013	1.022	1.022	1.031	1.013	1.022	1.02	1.023	1.022	1.022
United Kingdom	2014	.989	.989	.996	.982	.989	.988	.99	.989	.989
United Kingdom	2015	.974	.974	.979	.968	.974	.973	.974	.974	.974
United Kingdom	2016	.982	.982	.986	.978	.982	.982	.981	.982	.982
United Kingdom	2017	1.02	1.021	1.025	1.015	1.02	1.02	1.02	1.021	1.02
United Kingdom	2018	.97	.971	.983	.953	.968	.972	.969	.97	.968
United States	2011	1.027	1.028	1.029	1.024	1.027	1.03	1.023	1.028	1.027
United States	2012	1.017	1.018	1.021	1.013	1.017	1.019	1.015	1.018	1.017
United States	2013	1	1.001	1.003	.998	1	1.003	.997	1.001	1
United States	2014	1.009	1.009	1.012	1.007	1.009	1.012	1.005	1.01	1.009
United States	2015	1.007	1.008	1.01	1.005	1.008	1.011	1.004	1.008	1.008
United States	2016	.993	.993	.996	.99	.993	.996	.989	.993	.993
United States	2017	.999	1	1.002	.998	1	1.003	.996	1	1
United States	2018	1	1	1.002	.998	1	1.004	.995	1.001	1
Vietnam	2015	1.011	1.011	1.013	1.008	1.011	1.016	1.007	1.011	1.011