Online Appendix to "The Case for a Positive Euro Area Inflation Target: Evidence from France, Germany and Italy"

Klaus Adam (University of Mannheim, CEPR and CESIfo),

Erwan Gautier (Banque de France),

Sergio Santoro (European Central Bank and Banca d'Italia),

Henning Weber (Deutsche Bundesbank)

A Proof of Proposition 1

Appendix E.2.2 in Adam and Weber (2020) shows that - under the conditions stated in the proposition - hours worked in steady-state do not depend on the steady-state inflation rate. Household welfare thus only depends on consumption, which is given by

$$c(\Pi) = K\left(\frac{1}{\mu(\Pi)}\right)^{\phi}, \tag{1}$$

where $K > 0$ is a proportionality constant and $\mu(\cdot)$ the aggregate mark-up. Taking a second order expansion of the previous equation at the point $\Pi = \Pi^\star$ yields:

$$\begin{aligned} c(\Pi) = c(\Pi^\star) &- \left.\left(\phi c(\Pi)\frac{\partial\mu(\Pi)/\partial\Pi}{\mu(\Pi)}\right)\right|_{\Pi=\Pi^\star}(\Pi-\Pi^\star) \\ &+ \frac{1}{2}\left.\left(\phi\left(1+\phi\right)c(\Pi)\left(\frac{\partial\mu(\Pi)/\partial\Pi}{\mu(\Pi)}\right)^2 - \phi c(\Pi)\frac{\partial^2\mu(\Pi)/(\partial\Pi)^2}{\mu(\Pi)}\right)\right|_{\Pi=\Pi^\star}(\Pi-\Pi^\star)^2 + O(3). \end{aligned}$$

Since $\mu(\Pi)/\partial\Pi = 0$ at the point $\Pi = \Pi^\star$, we get

$$\frac{c(\Pi)-c(\Pi^\star)}{c(\Pi^\star)} = -\frac{1}{2}\phi\left.\frac{\partial^2\mu(\Pi)/(\partial\Pi)^2}{\mu(\Pi)}\right|_{\Pi=\Pi^\star}(\Pi-\Pi^\star)^2 + O(3),$$

which is equation (3) in proposition 1. The challenge consists of determining $\frac{\partial^2\mu(\Pi)/(\partial\Pi)^2}{\mu(\Pi)}$ in terms of deep model parameters. Appendix E.2.3 in Adam and Weber (2020) shows that

$$\frac{\partial \mu(\Pi)}{\partial \Pi} = \sum_{z=1}^{Z} \psi_z \mu_z(\Pi)^{\psi_z - 1} [\partial \mu_z(\Pi)/\partial \Pi] \left(\prod_{z^C} \mu_z(\Pi)^{\psi_z} \right) = 0, \tag{2}$$

where z^C denotes the set of all expenditure categories except for category z. Using the definition of the aggregate mark-up

$$\mu(\Pi) \equiv \prod_{z=1}^{Z} \mu_z(\Pi)^{\psi_z}$$

and the notation $\mu'(\Pi) = \partial \mu(\Pi)/\partial \Pi$, one can express equation (2) as

$$\mu'(\Pi) = \mu(\Pi) \sum_{z=1}^{Z} \psi_z \frac{\mu_z'(\Pi)}{\mu_z(\Pi)}, \tag{3}$$

Taking the derivative of equation (3) with respect to Π yields

$$\mu''(\Pi) = \mu'(\Pi) \left(\sum_{z=1}^{Z} \psi_z \frac{\mu_z'(\Pi)}{\mu_z(\Pi)} \right) + \mu(\Pi) \left(\sum_{z=1}^{Z} \psi_z \frac{\mu_z'(\Pi)}{\mu_z(\Pi)} \right)'.$$

At the point of approximation $\Pi = \Pi^\star$, we have $\mu'(\Pi) = 0$, so that

$$\left. \frac{\mu''(\Pi)}{\mu(\Pi)} \right|_{\Pi = \Pi^\star} = \sum_{z=1}^{Z} \psi_z \left(\frac{\mu_z'(\Pi^\star)}{\mu_z(\Pi^\star)} \right)'. \tag{4}$$

To compute the derivatives on the r.h.s. in the previous equation, we use the third equation in Appendix E.2.3 in Adam and Weber (2020), reproduced here for convenience, using the notation $b_z \equiv g_z/q_z$:

$$\frac{\mu_z'(\Pi)}{\mu_z(\Pi)} = \Phi_z(\Pi) \left[\Pi - b_z \frac{\gamma_z^e}{\gamma^e} \right], \tag{5}$$

where

$$\Phi_z(\Pi) = \frac{\theta \tilde{\alpha}_z \Pi^{\theta-2} \left(\frac{\gamma^e}{b_z \gamma_z^e} \right)}{\left(1 - \tilde{\alpha}_z \Pi^\theta \left(\frac{\gamma^e}{b_z \gamma_z^e} \right) \right) \left(1 - \tilde{\alpha}_z \Pi^{\theta-1} \right)}, \tag{6}$$

and where $\tilde{\alpha}_z = \alpha_z (1 - \delta_z)(\gamma^e/\gamma_z^e)^{\theta-1}$.

Using equation (5), we can determine the derivatives on the r.h.s. in equation (4). This yields

$$\left(\frac{\mu_z'(\Pi)}{\mu_z(\Pi)}\right)' = \Phi_z(\Pi)' \left[\Pi - b_z \frac{\gamma_z^e}{\gamma^e}\right] + \Phi_z(\Pi).$$

Substituting this expression into equation (4) yields

$$\left.\frac{\mu''(\Pi)}{\mu(\Pi)}\right|_{\Pi=\Pi^\star} = \sum_{z=1}^{Z} \psi_z \Phi_z(\Pi^\star)' \left[\Pi^\star - b_z \frac{\gamma_z^e}{\gamma^e}\right] + \sum_{z=1}^{Z} \psi_z \Phi_z(\Pi^\star). \tag{7}$$

Using the fact that $b_z \gamma_z^e / \gamma^e = \Pi^\star$ for all $z = 1, \dots Z$ at the point of approximation and the expression for $\Phi_z(\Pi)$ in equation (6), we obtain

$$\left.\frac{\mu''(\Pi)}{\mu(\Pi)}\right|_{\Pi=\Pi^\star} = \sum_{z=1}^{Z} \psi_z \frac{\theta \tilde{\alpha}_z \Pi^{\star\theta-3}}{\left(1-\tilde{\alpha}_z \Pi^{\star\theta-1}\right)\left(1-\tilde{\alpha}_z \Pi^{\star\theta-1}\right)}.$$

Using also the fact that $\widetilde{\alpha}_z \equiv \widetilde{\alpha}$ for all $z = 1, \dots Z$ at the point of approximation and that $\sum_{z=1}^{Z} \psi_z = 1$ delivers equation (4) in proposition 1.

B Data Appendix

This appendix describes the harmonized data transformations that we perform for all national micro price data sets alike and the country-specific characteristics of each data set (see appendices B1., B2. and B3.).

For each of the three economies, we employ the micro price data that underlie the official consumer price index (CPI). The data is at monthly frequency and contains product-level price information for goods and (private and public) services which are consumed by private households. For most products, price collectors visit different types of outlets and shops, or request price information and tariffs from the service sector in a decentralized manner. For some products, price collection is centralized and refers to publicly available sources such as the internet. The data also contain survey-based information on expenditure shares that a typical household in the respective country spends on a product category.

In the analysis, we consider only price observations that enter the computation of the national CPI, and omit all price observations flagged as not originally sampled, i.e., imputed or interpolated price observations. To harmonize the product definition across countries, we refine the product definition originally provided by national statistical institutes as follows. We split the price trajectory of an original product whenever price observations are missing for more than one month (including missing quotes that results from dropping imputed prices); comparable or non-comparable product substitutions occur; and product quality or quantity sold (such as package size) change. As described in the main text, we use expenditure weights to aggregate statistics across expenditure categories. We compute the normalized average expenditure weight according to

$$\psi_z = \frac{\frac{1}{T_z - t_z + 1} \sum_{t=t_z}^{T_z} \widetilde{\psi}_{zt}}{\sum_{z=1}^{Z} \frac{1}{T_z - t_z + 1} \sum_{t=t_z}^{T_z} \widetilde{\psi}_{zt}}, \tag{8}$$

where $\widetilde{\psi}_{zt}$ is the expenditure weight of category z at time t, t_z is the first observation in this category for a given economy and T_z is the last observation in this category.

B1. French Data

We rely on the longitudinal dataset of monthly price quotes collected by the Institut National de la Statistique et des Études Économiques (INSEE) to compute the monthly French CPI and HICP. The raw data set contains about 9.5 million price quotes for the baseline period from October 2014 to September 2019 and 7.6 million price quotes for the reference period from October 2009 to September 2014. Centrally collected prices, such as car prices, administered prices (e.g. tobacco), public utility prices (e.g. electricity), and rents, are not part of the data set. Individual products are classified in about 4000 product categories at the most disaggregate (elementary) level of product classification, which is used to compute elementary price indices. These categories are grouped in 334 COICOP categories at the 6-digit level and 230 ECOICOP categories at the 5-digit level.

The price variable employed in the present analysis are the prices that enter the computation of elementary price indices (i.e., quality/quantity-adjusted prices of individual products sold in shops). The data set also contains information to recover the collected price (i.e., before quality/quantity adjustments) and various flags indicating changes in quantities or packaging. Furthermore, the data flags imputed prices. Prices are imputed for seasonal products that are out-of-season, when products are temporarily unavailable, or when products are in the process of being replaced. A qualitative variable in the data set documents the reasons for having a "non-normal" observed price (which does not necessarily mean price imputation): product is temporarily not available (6%); outlet is temporarily closed (1.5%); no valid replacement outlet is available (0.5%); no price collection (1.5%); non-comparable product substitution (3%); and comparable product substitution (2.5%).

Data for official monthly price indices, HICP expenditure weights at the 5-digit ECOICOP level and national CPI expenditure weights at the 6-digit ECOICOP level is obtained from the INSEE website.

Data preparation. We drop the price quotes that are imputed by INSEE. About 15% of all price quotes are imputed, with the bulk of imputations in food categories or non-energy industrial goods. Most prices are imputed only for very short periods of time, for example because of temporary shop closing. Longer price imputation spells are observed in categories with seasonal products, but are overall rare. Dropping imputed prices leaves us with 8 million observations in the baseline sample and 7 million observations in the sample covering the period 2009-2014.

Product definition and regression analysis. In the French data, the individual product identifier allows to track prices for a given product over time and any product replacement (comparable or not) over the period of the price collection for this product. In particular, INSEE flags a comparable or non-comparable product substitution but also provides information allowing to track by which new product an old product has been replaced (in case of forced substitution). We refine the original product identifier by splitting price trajectories into subcomponents, as described in the beginning of appendix B. This increases the number of products from about 641k products to 736k products for the 2014-2019 sample and from 489k products to 544k products for the 2010-2014 sample.

For the baseline specification of the regression equation (2), we compute relative prices using the cross-sectional average price calculated at the most disaggregate (elementary) level. For robustness, we also compute relative prices using official price indices for the 5-digit ECOICOP level.[1] For most categories in the baseline sample, slope estimates from the baseline regression correlate highly with slope estimates from the alternative specification that uses the official price index to deflate product prices. However, for some categories, substantial differences between slope estimates emerge because in these cases, price deflators exhibit different dynamics and/or volatility. Thus, for French baseline results, we drop 10 (out of 4000) elementary categories and three (out of 300) 6-digit COICOP categories ('Natural gas' 04.5.2.2.1, 'Pharmaceutical products' 06.1.1.0.1 and 'Canteens' 11.1.2.0.1). The three categories represent about 4% of total expenditure in the product basket. For the 2009-2014 sample, we drop one category ('Camper vans, caravans and trailers' 09.2.1.1.1) for the same reason.

Expenditure weights used for aggregation. We aggregate statistics from the elementary level to higher levels in three steps. First, we compute the simple average of statistics at the elementary level to obtain statistics at the 6-digit COICOP level. Second, we use national expenditure weights at 6-digit COICOP level to obtain weighted aggregate statistics at 5-digit level. Finally, we use French HICP expenditure weights at 5-digit COICOP level to obtain statistics at the 2- or 3-digit COICOP level or for the aggregate level.

[1] This is the most disaggregated level at which INSEE publishes official price indices at a monthly frequency.

B2. German Data

We use the German monthly micro price data that underlie both the computation of the CPI and the HICP. Most price observations are collected by Statistical Offices of the German Federal States, where each statistical office collects product prices for its state.[2] In most product categories, prices are collected decentralized in physical outlets. For some product categories, however, price collection is centralized and thus takes place either at the federal level or by a single state office for all federal states together.[3] Product prices are collected in each month, preferably in the middle of the month. Information on product prices and expenditure weights is accompanied by information on quality adjustments (in Euros) and quantity adjustments of product prices. This information is provided by price collectors and reflects changes in product characteristics or package size. In our analysis, we only employ quality/quantity-adjusted product prices. Individual products are classified according to 10-digit COICOP.

Data preparation. The following describes preparation of the baseline sample from 2015:01 to 2019:12. Data for the 2010:01 to 2014:12 sample is prepared identically. The raw data for the baseline sample contain 36 million observations. We restrict this sample to price observations which are also used to compute the official CPI and drop observations with tiny prices (less than 5 cents) and observations for which the price deviates by more than minus 99% or plus 10000% from the average price at the stratum level.

We further restrict the sample to 10-digit COICOP categories with price observations collected for more than one outlet and more than one product to obtain meaningful relative price regressions.[4] We also exclude 10-digit COICOP categories for which official price indices

[2]Data are provided by the Research Data Center (RDC) of the Federal Statistical Office and Statistical Offices of the Federal States, "Einzeldaten des Verbraucherpreisindex 2018," EVAS-Nummer 61111, 2010 - 2019, DOI:
10.21242/61111.2010.00.00.1.1.0 to 10.21242/61111.2019.00.00.1.1.0.

[3]The Federal Statistical Office (Destatis) also collects product prices centrally for all federal states jointly. These price observations are not part of our data set.

[4]In particular, we exclude 731111100 Bahnfahrt, Nahverkehr; 820200200 Mobiltelefon ohne Vertrag;

are not available, which allows us to complement our baseline regression specification with an alternative specification.[5]

From the resulting sample, we drop the price observations that are imputed by Federal Statistical Offices.[6] About 5.9% of all price observations in the raw data are imputed, with a larger share of imputed price observations in categories for seasonal products, such as clothing. After these adjustments, the data set contains 30 million price observations, classified in approximately 700 expenditure categories at 10-digit COICOP level. At this stage of the analysis, the informational content of the German 10-digit COICOP is equivalent to the German 8-digit COICOP.

Product definition. In the German data, the original product identifier provided by Federal Statistical Offices yields a unique mapping of price observations to individual products. We refine the original identifier by splitting price trajectories into subcomponents as described in the beginning of appendix B. We also drop all products (refined identifier) with less than two price observations. Refining the product definition in this way increases the number of products from 808k to 2.37 million.

Expenditure weights used for aggregation. We aggregate statistics from the 8-digit COICOP level to higher levels in two steps. First, we use national expenditure weights at the 8-digit COICOP level to compute weighted aggregate statistics at 5-digit COICOP level. Second, we use harmonized expenditure weights at 5-digit COICOP level to compute even

913221100 Tintenstrahldrucker; 913221200 Laserdrucker; 1111203400 Speise zum Verzehr in öffentlichem Verkehrsmittel; 1111203500 Getränk zum Verzehr in öffentlichem Verkehrsmittel.

[5] We obtain official price indices for the baseline sample from `https://www-genesis.destatis.de/genesis/online?operation=previous&levelindex=3&step=2&titel=Tabellenaufbau&levelid=1611219556060&levelid=1611219502477#abreadcrumb`.

[6] Imputation events are the following: a seasonal product out-of-season; product temporarily not available; non-comparable product substitution; replacement product declined; abstain from replacement product; no valid replacement product available; outlet temporarily closed; replacement outlet declined; abstain from replacement outlet; no valid replacement outlet available.

more aggregate statistics, such as those in table 1 in the main text.[7]

Sample comparison. For reasons of data availability, we do not use disaggregate official price indices to compute relative product prices in equation (2) when we compare estimates of the optimal inflation rate over time (see table 1). Instead, in this case, we compute relative product prices using elementary price indices which are part of the German micro price data. For the baseline sample from January 2015 to December 2019, both elementary and official price indices are available and yield essentially identical estimates for the optimal inflation rate.

B3. Italian Data

We use the monthly micro price data that underlie the computation of the CPI and the HICP. The data is provided to us by the Italian National Statistical Institute (ISTAT). In particular, we use prices collected locally once a month by municipal statistics offices in over 70 provincial capitals; hence our sample neither includes prices collected centrally (e.g., cars), nor those collected locally more than once a month (e.g., some unprocessed food). The baseline sample spans the 4-years period January 2016 - December 2019, and contains around 3.3 million observations per year. Prices collected belong on average to 612 10-digit COICOP categories, grouped in 263 8-digit COICOP categories. Besides information on product prices, the Italian micro data also contain information on imputation, sales and product replacement. The price variable we use in the analysis is the price collected at stores, divided by the corresponding quantity (to account for changes in packaging). The data on official indices and expenditure weights at the 8-digit COICOP level are provided by ISTAT; both indices and expenditure weights are those used to compute the official HICP index, and differ from the national CPI statistics mainly for the treatment of sales and health-related

[7] Harmonized expenditure weights at 5-digit COICOP level come from the ECB statistical data warehouse, `https://www.ecb.europa.eu/stats/ecb_statistics/escb/html/table.en.html?id=JDF_ICP_COICOP_INW`.

items.

We choose to consider in the baseline sample only data starting from January 2016, as between 2015 and 2016 the classification of Italian consumer prices data adopted by ISTAT underwent a substantial change, reflecting the wider adoption of the new classification ECOICOP (European Classification of Individual Consumption by Purpose). Before 2016, the Italian classification coincided with ECOICOP only up to the 4-digits level, while from January 2016 it also coincided at 5- and 6-digits categories, which causes some categories to non-connectable over the 2015-2016 period.[8]

Data preparation. From the raw data we drop the imputed price quotes, as indicated by imputation flags. A price is imputed by ISTAT if (i) a store is closed, either temporarily (e.g., during summer vacations) or for good; (2) an individual product sampled in a store is not present, either temporarily for reasons different from seasonality or for good; (3) the product is out-of-season (for seasonal products); (4) the price could not be collected for extraordinary reasons;[9] (5) missing observations for other reasons. Slightly less than 9% of all price observations are imputed; more than one half are imputations due to seasonality, especially concentrated in categories such as clothing. We control for outliers dropping some prices that take very high values, and dropping the observations smaller than the 1st percentile and larger than the 99th percentile of the price distribution computed for each month of the sample at the 10-digit COICOP level.

Product definition and regression analysis. The meta data available for each elementary price enable us to track the price of a product (defined at the 10-digit COICOP level) of a given brand at a given retailer over time, i.e. to trace what we call a price trajectory. We refine the original identifier by splitting price trajectories into subcomponents as described

[8] For more details on the classification change, see the methodological note at `https://www.istat.it/it/files//2016/02/EN_Basket_2016.pdf`.

[9] This last flag has been extensively used during the 2020 lockdown, when collectors could not go to the stores to collect prices.

in the beginning of appendix B. Refining the product definition in this way increases the number of products from around 407k to 655k. At this stage, we also drop all price observations that belong to refined product identifiers with less than two price observations. Dropping products with less than two observations, imputed prices, and outlier observations reduces the number of observations from roughly 13.3 million to 11.7 million.

We run the regressions in equation (2) under two possible specifications; in both of them we define relative prices and run the regressions at the 8-digit COICOP level. In the baseline specification, we compute relative prices using as denominator the average of collected prices. In the second specification, we compute relative prices using official price indices as denominator. In computing aggregate results, we drop the coefficients of the 8-digit category related to garden furniture (code 05.1.1.2.0.00), as it is present only in 2019 and shows abnormally wide price swings, and the coefficients of a 10-digit COICOP category related to long-term public parking, as it is highly dependent on a sharp price change adopted in a single province (code 07.2.4.2.1.00.03).

C The Optimal Inflation Targets Over Time

This appendix analyzes the trend of optimal inflation targets over time in the considered countries. To this end, we compare estimates of the optimal inflation target obtained from the baseline sample period (2015/6-2019) to the corresponding estimates obtained from an earlier sample period (2010-14 for France and Germany, 2012-2015 for Italy).

The sample comparison is complicated by the fact that national statistical institutes changed the basket of expenditure categories underlying national CPIs as well as the base period at the end of 2014. In addition, the integration of European harmonized expenditure weights into national statistics took place around the same time, but introduction dates varied across countries and also depended on the level of disaggregation.

As a result of these reclassifications and changes, only a relatively small set of COICOP

	France		Germany		Italy	
	2010-14	2015-19	2010-14	2015-19	2012-15	2016-19
Baseline approach:	1.5%	1.2%	1.7%	1.2%	1.3%	1.4%
Official price index for P_{zt} in equation (1):	1.4%	1.3%	1.1%	1.1%	1.6%	1.0%

Table 1: The optimal inflation target over time (country-specific samples harmonized over time)

categories is available across all three countries and across both sample periods jointly, which makes comparisons that are valid across countries *and* across time unattractive, as they would have to rely on a rather small subset of the data.

Given these data constraints, we focus our analysis on a reliable time comparison by selecting the largest set of COICOP categories that is available in both sample periods for any given country under consideration. As a result, the estimates for the baseline sample period (2015/16-2019) obtained in the present section will differ from the ones presented in tables 3 and 4.

Matching the expenditure categories at the country level (COICOP8 level for Germany and Italy, elementary level for France), we cover 64.6% of the official expenditure basket for France, 74.5% for Germany, but only 27.5% for Italy.[10] To isolate the effect of changes in the slope coefficient b_z over time, we use the expenditure weights (ψ_z) and growth rate weights (γ_z^e/γ^e) from the latter sample period (2015/6-20) to compute the optimal inflation rates in the earlier sample period.

Table 1 reports the outcomes for the optimal inflation rates over time. For the case where the slope coefficients b_z are estimated using the average price for P_{zt} in equation (2), there is

[10]Table 2 in Appendix D reports the descriptive statistics for the resulting samples. The table shows that for each country, the two sample periods are very similar in terms of the number of observations and the number of products.

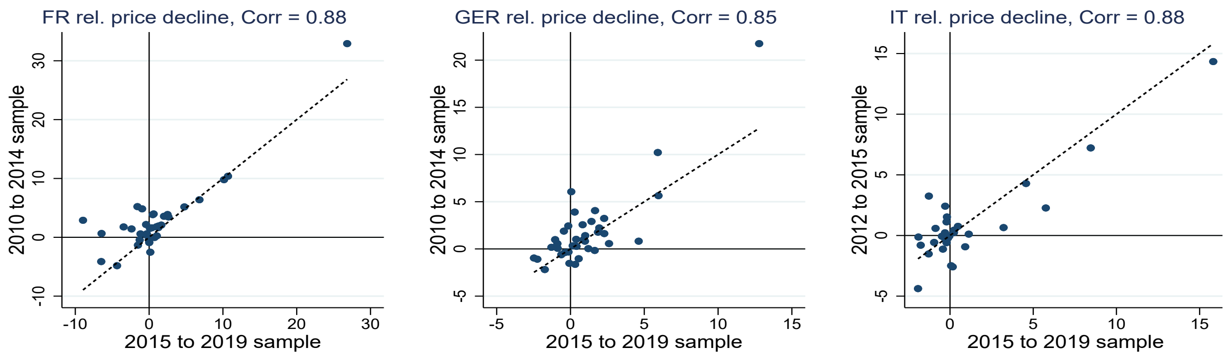

Figure 1: Optimal inflation rates at the COICOP3 level over time (country-specific samples harmonized over time)

a general tendency for the optimal inflation target to fall. This effect is quite pronounced in Germany but also present in France. Italy displays a very small increase, but this is based on a much smaller coverage of the expenditure basket. When the slope coefficients b_z are estimated using the official price index for P_{zt} in equation (2), the decrease in the optimal inflation targets largely disappears in France and Germany but the Italian estimates now display a considerable decrease.[11]

Overall, these somewhat mixed results suggest that the optimal inflation rate might have declined over time or could have been broadly stable. Reassuringly, however, the estimates for the earlier sample period are in the same ballpark as the estimates in the latter period, which shows that relative price trends tend to display considerable stability over time. This fact is further illustrated in figure 1, which depicts the optimal inflation rates at the level of COICOP3 expenditure categories across time for each of the three countries. As indicated by the 45 degree lines in the figure and the correlations reported at the top of each panel, there is a surprisingly strong positive comovement of the optimal inflation rates over time at this disaggregated expenditure level.

[11] For reasons of data availability, we compute relative prices for Germany in the earlier period using elementary price indices, see sample-comparison appendix B2..

	France		Germany		Italy	
	2010-14	2015-19	2010-14	2015-19	2012-15	2016-19
Total # of price quotes	6.4m	6.2m	22.8m	26.6m	2.2m	2.2m
# of COICOP5 categories	214	214	197	197	94	94
Coverage of HICP basket	.	64.6%	.	74.5%	.	27.5%
# of quotes per COICOP5						
Mean	29.8k	28.8k	115.6k	134.9k	23.4k	23.7k
Median	15.6k	13.4k	53.9k	63.8k	19.0k	19.6k
# of products per COICOP5						
Mean	2.4k	2.3k	8.9k	10.6k	1.3k	1.3k
Median	1.0k	1.0k	2.3k	2.4k	1.2k	1.1k

Table 2: Descriptive statistics for samples with harmonized set of COICOP5 categories over time, but not across countries.

D Additional Tables and Figures

This appendix provides additional descriptive statistics and figures to complement the analysis in the main text. Table 2 provides descriptive statistics for the two sample periods for each country, with harmonized set of COICOPs over time, but not across countries. These samples underlie the estimates of the optimal inflation rate in section C. The table omits the covered expenditure share of the HICP basket for the early sample because harmonized expenditure weights at 5-digit COICOP level are available only for the later sample.

Figure 2 presents the joint distributions of optimal inflation rates across countries at the COICOP3 level. It is the non-truncated version of figure 4 discussed in the main text in section 6.3..

References

Adam, K., and H. Weber (2020): “Estimating the Optimal Inflation Target from Trends in Relative Prices,” ECB Working Paper No. 2370.

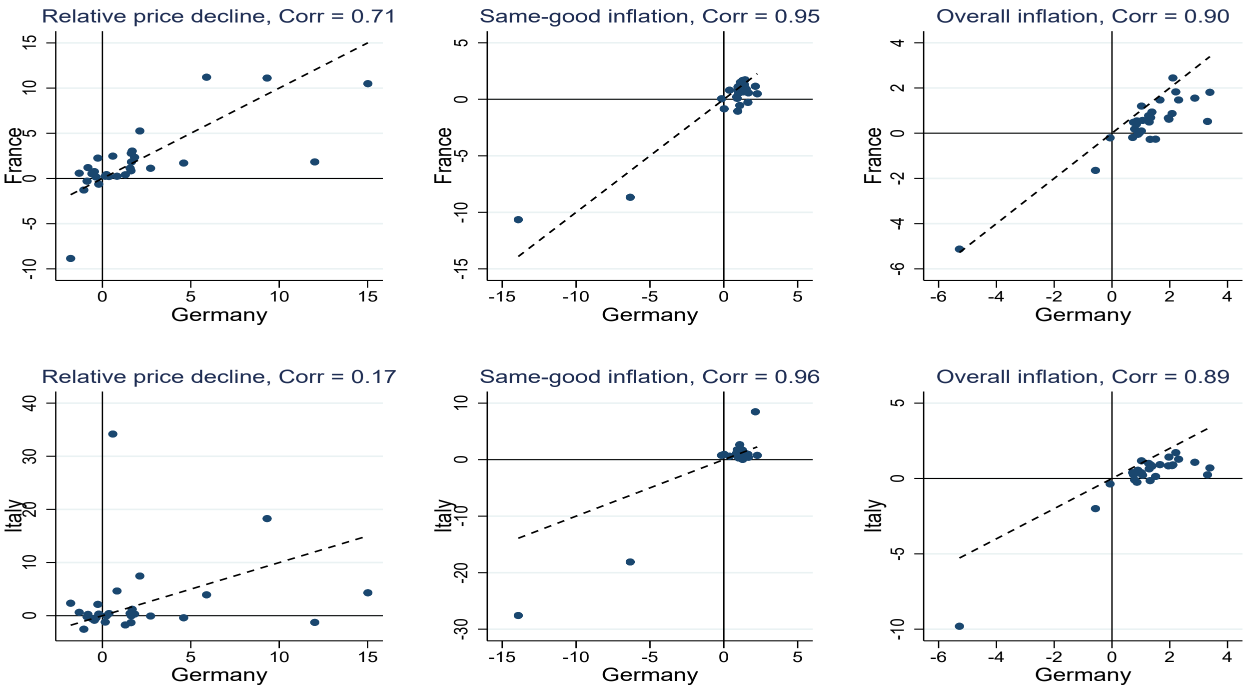

Figure 2: Non-truncated version of figure 4