Toward a general framework for constructing and evaluating core inflation measures*

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Abstract

There is no unifying framework for evaluating core inflation measures, so we propose a general framework to close this gap. Our methodology uses disaggregated data of consumer price index, and hinges on a standard quadratic loss function. We show that the usual indicator that excludes food and energy, which is the most widespread measure of core inflation for Central Banks, performs poorly across the five countries analyzed, due to substantial bias, low persistence, high volatility, and low forecasting power. Therefore, our recommendation is to revise its use. By optimally selecting the CPI components to be excluded with our methodology, the properties of core inflation measures can be significantly improved. Finally, we argue that when there is a preference regarding the use of fixed exclusion measures, nothing is lost and much can be gained by optimally selecting the excluded items, instead of sticking with the usual adhoc criteria.

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1 Introduction

Month-on-month (MoM) inflation is regularly monitored by Central Banks to assess the state of the economy. However, it is too volatile to be used as a reference for short-term monetary policy decisions. Volatility stems from multiple factors: temporary supply shocks in specific sectors and measurement errors, among others. Alternative inflation measures, known as *core* or *underlying*, filter out part of the noise that obscures the stable inflation signal that policymakers pursue to make sound decisions.[1] As Hogan et al. (2001); Roger (1997); Wynne (1999); Shiratsuka (1997); and Cutler (2001) argue, core inflation is the object of interest for monetary policy decision-making.

The literature highlights two main strategies for constructing core inflation measures. The first consists of down-weighting noisy components, and the second uses statistical methods for time-series smoothing in order to extract a stable signal of inflation. Central Banks usually prefer the first strategy because it simplifies the accountability and communication of monetary policy decisions to the public. In this paper, we follow this tradition at Central Banks and restrict the analysis to the first strategy.

Our objective is to propose a general methodological framework to construct and evaluate core inflation measures and to assess how it works by applying it to countries with different characteristics.

Three reasons motivate us to reconsider core inflation measures, which is admittedly an old topic. First and foremost, as we show below, the usual adhoc strategies that exclude volatile components, such as food and energy, may be seriously misguided. This is because excluding volatile components may affect the properties of the resulting aggregate, so that we may end up analyzing (and making policy decisions base on) an indicator that is, for instance, biased, too volatile, and/or lowly persistent. We claim that the decision regarding which components are to be excluded must be conditional on the properties of the resulting aggregate.

Second, there is ongoing discussion of why the relationship between inflation and economic slack predicted by the Phillips curve is not showing up in the data (see, e.g., Moretti et al., 2019, Orphanides and Williams, 2004). To empirically assess this problem, a well-behaved core inflation measure is a crucial input.

Finally, there is an argument in terms of timing. Several Central Banks around the world have revisited their monetary policy frameworks, including their objectives and instruments. For instance, the Central Bank of Chile, the European Central Bank, and the FED in 2020, and the Bank of Canada in 2021, among others. In the process of updating these frameworks, research produced abundant analytical and empirical evidence on key variables, and particularly on core inflation measures. In this regard, a unifying framework for evaluating core inflation measures across countries would be useful for international comparisons.

With respect to the stated motivations, this paper makes two contributions. First, we propose a generic methodological framework for constructing and evaluating core inflation measures (in a way that extends e.g. Lao and Steyn, 2019; Johansson et al., 2018; Ehrmann et al., 2018; and Silver, 2007). We believe our approach is appealing as it considers an explicit loss function that combines multiple "targets" based on statistical properties of core measures and allows us to both decide on the optimal down-weighting and rank alternative core measures. The idea is simple: A loss function, defined by the policymaker, may clearly balance and rank alternative core inflation measures, even if different measures overlap in terms of particular statistical properties. Hence, evaluation of the loss provides a synthetic index that combines several dimensions. In this sense, our contribution contrast with recent papers that

[1] See, for example, Clark (2001) for an overview of core inflation measures.

consider core inflation's properties one by one.[2]

Second, we apply our methodology to a group of developed and emerging countries (Chile, Colombia, Peru, the Euro Area, and the US).[3] The evidence suggest that our method lead to conclusions that are in general robust across the countries examined.

Our findings show that by optimally selecting the components to be excluded, properties of core inflation measures can be substantially improved. In addition, our strategy also leads to exclusions and down-weightings that make sense from an economic point of view. As mentioned above, we document that the most widespread core inflation measure used by Central Banks and statistical agencies — which excludes food and energy from the CPI (CPIXFE)— tends to show poor performance in all the countries we consider.

The rest of the paper is organized as follows. In §2 we document stylized facts of empirical distributions of CPI components. In §3 we provide basic definitions, and §4 presents the methodology proposed. In §5 we present empirical results. Finally, §6 concludes.

2 Stylized facts

This section documents stylized facts of US CPI inflation, broken down into 173 components, to illustrate some general empirical features of the cross-sectional distribution.We found similar facts for the other countries we consider; for brevity, a summary of them is included in appendix A.

The first two graphs of Figure 1 illustrate the full cross-sectional distributions of components' annual variation in two arbitrary months of the sample. Two relevant insights emerge. First, the distributions are highly non-normal because of both excess kurtosis and asymmetry. Second, comparison of these two distributions suggests that they are unstable along time. For instance, whereas in October 2005 kurtosis was 75.8 and asymmetry 7.6, in February 2018 these values moved to 9.4 and -1.4, respectively.

The remaining graphs of Figure 1 illustrate the time evolution of kurtosis and asymmetry in the sample and confirm the instability of cross-sectional distributions. Additionally, extreme events (months with components whose variations are far from the mean, represented by the three peaks in the kurtosis) have always been inflationary, as they coincide with peaks of positive asymmetry.

These features of the cross-sectional distributions of CPI components, which are not specific to the US (see Figure A.1 of appendix A), are the main cause of a usual, albeit not well-founded, practice of Central Banks and private analysts. Each time a new inflation data point constitutes a surprise, analysts assess whether the surprise has been general to a large number of components or is associated with only a few. In the latter case, the analysis of the new data point usually includes assessments of the evolution of headline inflation excluding the 'problematic' items.

This common strategy has two important limitations. First, and foremost, once we exclude some components of the CPI, we may substantially affect the statistical properties of the resulting aggregate, as we document later on. Second, the exclusion criteria are unsystematic and dependent on the analyst's opinion —and, therefore, difficult to communicate to the market. Our proposal seeks to make this practice systematic and accountable, and to ensure

[2]Examples of recent papers that propose novel methods to compute core inflation but analyze properties in sequence are Conflitti (2020); Luciani and Trezzi (2019); Gamber and Smith (2019); Dolmas and Koenig (2019); Acosta (2018); among others.

[3]For example, see Gartner and Wehinger (1998) which estimates core inflation measures in a cross-section of countries.

that the resulting core measure satisfies certain quality conditions.

3 Basic definitions

In this section we define the set of core inflation measures we consider.

The general aggregation formula for constructing headline CPI inflation from its components is

$$\pi_t = \sum_{i=1}^{N} w_{it}^{*} \pi_{it}, \tag{1}$$

where π_t stands for headline MoM inflation, π_{it} is the MoM variation of the i-th component; w_{it}^{*} is the *implicit weight* of the i-th component, which is defined as $w_{it}^{*} = w_i \frac{P_{it-1}}{CPI_{t-1}}$, with w_i being the share of the i-th component in the representative consumer's total expenditure; P_{it-1} the price level of the i-th component at time $t-1$; and N the total number of components.

Within the general approach of re-weigthing components, various strategies have been proposed in the literature. The most widespread assigns zero weights to energy and food items to calculate core CPI (e.g., Gordon, 1975; Eckstein, 1981). In Chile, Colombia, Peru, Euro Area (EA), and US this measure represents approximately 72%, 77%, 56%, 70%, an 89% of the CPI, respectively.

Bryan and Pike (1991) propose using the *weighted median* of MoM variation of the components as an indicator of core inflation. The proposal is appealing due to the observation that the distribution of the MoM component's inflation is usually very asymmetric (see previous section). To construct this indicator, the components are ordered ascendingly according to their MoM seasonally adjusted variation. Then the first component that accumulates at least 50% of the weight is defined as the median component and its variation as the weighted median inflation of the corresponding month. This procedure is repeated each month, so that the component located at the median may be a different one at each month of the sample.[4]

As argued by Bryan and Cecchetti (1994), the weighted median is a particular case within a class of more general central tendency estimators. The authors propose construction of a *trimmed mean*. At each month of the sample, the components located at the tails of the distribution of MoM variations receive zero weighting. The trimmed components will vary month to month. The weighted median would therefore be an extreme case of a trimmed mean, in which all components are trimmed except the one located at the median.

Denoting α_0 and α_1 the proportion of the weight to be trimmed on the left and right tails, respectively, Bryan and Cecchetti (1994) choose $\alpha_0 = \alpha_1 = 7.5\%$.

In general, trimmed means, π_t^{*}, are computed as follows:

$$\pi_t^{*} = \sum_{i=1}^{N^{*}} w_{it}^{tm} \pi_{it}, \tag{2}$$

where $w_i^{tm} = \frac{w_{it}^{*}}{\sum_{i=1}^{N^{*}} w_{it}^{*}}$ and N^{*} is the number of CPI components that survive the trimming.

A variant of trimmed means consists of trimming the components for which the standard deviation of its seasonally adjusted MoM growth rate, computed for the last h months, is located on the right tail (see Pedersen, 2006). Thus, instead of trimming the components with the greatest variation in a given month, the most volatile components that accumulate a proportion α of the total weight are trimmed. We will denote this strategy *trimmed*

[4] Ball and Mazumder (2019) advocate the use of median inflation by policymakers.

mean by variance.

A second variant of the trimmed mean consists of not assigning zero weighting to any component but rather adjusting the weights according to the recent volatility of their MoM growth rates. The greater the volatility, the greater the downward adjustment (see Khan et al., 2015). We term this strategy *mean adjusted by variance*, or MAV for short.

Under this strategy, core inflation (π_t^*) is constructed as

$$\pi_t^* = \sum_{i=1}^{N} w_{it}^{mav} \pi_{it}, \tag{3}$$

where $w_i^{mav} = \frac{\lambda_i}{\sum_{i=1}^N \lambda_i}$, $\lambda_i = \frac{w_{it}^*}{\sigma_{it,h}^2}$, $\sigma_{it,h}^2 = \frac{1}{h-1} \sum_{j=t-h+1}^{t} (\pi_{ij} - \mu_{ih})^2$, con $\mu_{ih} = \frac{1}{h} \sum_{j=t-h+1}^{t} \pi_{ij}$.

The median, all trimmed means, and the adjusted mean exclude or down-weight components that differ from month to month. This may render communication to the general public somewhat involved. For the sake of keeping communication as simple as possible, we propose an optimal fixed exclusion measure (OFE). This is analogous to the trimmed mean, except that components to be excluded are fixed, but selected using the optimal criteria we define in next section.

Table 1 summarizes the six measures considered in this paper. As is clear, while the trimmed means and the optimal fixed exclusion measure require selecting some parameters for their construction (trimming proportions and the time window for estimating volatility), the rest of the measures do not. The final column of the table lists whether the measures are calculated using a fixed exclusion of components.

4 Our proposal

To determine trimming proportions and/or volatility estimation windows, the usual practice in the literature is to use adhoc criteria or adopt the parameters used by other authors. Bryan et al. (1997); Vega and Wynne (2003); and Córdova et al. (2008) are exceptions to this rule; they select the parameters so that the core measure is as close as possible to a predefined benchmark.

We propose a different strategy: Choosing the trimming parameters such that the resulting core measure offers good statistical properties. The methodology provides a useful procedure to formalize and systematize what sometimes may be done in an adhoc way by practitioners —this is, to exclude specific components that may have shown unexpected extreme variations, typically volatile food and energy items. The risk is that adhoc choices may lead to end up analyzing a core inflation with bias, low persistence, or/and high volatility, all undesirable statistical properties. By choosing the trimming parameters that minimize a loss function on the desired statistical properties, we seek to endogenously ensure the good properties of the resulting core measure.

Specifically, well-behaved core inflation measure should hold the following properties (see, e.g., Lao and Steyn, 2019 for a discussion of the desirable properties of core measures): (i) high persistence or smoothness, which we denote as ρ; (ii) low volatility, which we denote as σ; (iii) small bias with respect to total inflation, so that the mean (μ) must be as close as possible to that of headline inflation or the monetary policy target; and (iv) low error in forecasting headline inflation, which we denote $RMSFE$ (for root mean square forecast error). Next, we discuss the precise statistics used for measuring each property.

4.1 Measurement of desirable properties

Persistence

The persistence of the MoM core inflation indicator, π_t^*, is denoted by ρ and will be measured as the value of the largest root of the autoregressive polynomial $\Phi(L)$ on the lag operator L:

$$\Phi(L)\pi_t^* = c + \epsilon_t, \tag{4}$$

where $\Phi(L) = (1 - \phi_1 L - ... - \phi_p L^p)$ and p is chosen based on the Akaike information criteria, AIC.[5]

Volatility

The unconditional variance of π_t^* depends positively on its persistence. To isolate the effect of persistence on variance, we will use the standard deviation of ϵ_t on Equation (4) as the indicator of volatility (σ).

Bias

In our setting, bias is defined as $b = 1200 \times (\mu - \mu_0)$, where μ and μ_0 are the sample means of MoM core and headline inflation, respectively. Alternatively, μ_0 can be defined as the inflation target of the Central Bank.

Forecast error

We design a recursive out-of-sample exercise and use each core inflation indicator to forecast headline inflation, as follows:

$$\hat{\pi}_{t+h} = c + \Theta_h(L)\pi_t^* + \Phi_h(L)\pi_t + \epsilon_t, \tag{5}$$

where, $\hat{\pi}_{t+h}$ is the forecast of headline inflation for the period $t+h$ with information available up to t. $\Phi_h(L) = (\phi_{h,0} + \phi_{h,1}L + \phi_2 L^2 + ... + \phi_{h,p}L^p)$, $\Theta(L) = (\theta_{h,0} + \theta_{h,1}L + ... + \theta_{h,m}L^m)$ and the length of polynomials is chosen using the AIC. The sample period to evaluate the forecasting performance is 2012.1 - 2019.12.

The exercise is recursive. We first cut the sample at 2012.1 and compute forecasts from $h = 1$ to $h = 6$. Then we add one observation, reestimate the forecasting equation, and obtain another set of forecasts. The statistic to be included in the loss functions is the root mean squared forecast error for $h = 6$:

$$RMSFE = \sqrt{\frac{1}{T-6-t^*}\sum_{t=t^*}^{T-6}(\hat{\pi}_{t+6}^6 - \pi_{t+6}^6)^2}, \tag{6}$$

where t^* is the number of observations up to 2012.1, and π^6 and $\hat{\pi}^6$ denote accumulated effective and forecast inflation, respectively.

4.2 The proposal

We propose selecting trimming parameters using a loss function that penalizes deviations of the four aforementioned properties from their 'desired' levels. The loss function takes the following form:

[5] Seasonal unit roots tests, *à la* Osborn et al. (1988), in general, reject the existence of seasonal unit roots in the CPIs and their components (see Carlomagno and Espasa, 2021, for similar results on the US CPI). Therefore, although the objective is to have a core indicator whose *annual* variation shows high persistence, Equation (4) is estimated over the MoM inflation to avoid the presence of non-invertible moving averages and temporal aggregation problems (for an analysis of these problems see Granger and Siklos, 1995; for a justification of the strategy described, see Marcellino, 1999).

$$L_i = V_i \times W \times V_i', \tag{7}$$

where L_i denotes the value of the loss function for core indicator i, vector V_i gathers distances for each of the properties with respect to the desired values, and the square matrix W contains appropriate weights to balance the loss. The vector of distances is specified as

$$V_i = [(\rho_i - \rho_0), (\sigma_i - \sigma_0), b, (RMSFE_i - RMSFE_0)], \tag{8}$$

where subscripts '0' denote desired values. Assuming that we have J core inflation indicators under consideration, we define desired values as

$$\begin{aligned} \rho_0 &= max_j([\rho_1, ..., \rho_J]), \\ \sigma_0 &= min_j([\sigma_1, ..., \sigma_J]), \\ RMSFE_0 &= min_j(RMSFE_1, ..., RMSFE_J). \end{aligned} \tag{9}$$

The parameter selection process consists of building a large number of π_t^* indicators with different combinations of parameters and choosing the combination that minimizes the loss function defined in Equation (7).

For selecting the trimming parameters α_0 and α_1 (see Table 1), we consider J = 1,681 combinations that arise from allowing any of the 41 possible values in the range [0.05 : 0.45]; considering jumps of 0.01 for each parameter. For α, we allow the 86 values in the range [0.05 : 0.90] with discrete jumps of 0.01.[6] For h, we consider values $[6, 12, 18, 24]$ (which implies 324 possibilities for the combination (α, h), so that $J = 324$). After constructing each of the six core measures defined in Table 1 and considering the whole range of parameters, we use the loss function first to compute the optimal parameters for core measures, and then to compare their properties (the algorithm is described in more detail in next section).

It only remains to define the weighting matrix, whose values should reflect the preferences of the policymakers. A neutral stance would be assigning equal weights to every property, what can be done by setting W equal to the identity matrix of dimension 4.

4.3 The algorithm

The algorithm for constructing the core measures can be summarized in Table 2.

5 Empirical applications

5.1 Data

For the Chilean CPI, we use monthly data provided by the National Bureau of Statistics (INE)[7], brokendown into 144 'sub-clases', for the period January 2002 to December 2019. We use seasonally adjusted data obtained from the filter X13-ARIMA.

For the US we use the current seasonally adjusted data for all Urban Consumers reported by the Bureau of Labor Statistics (BLS), at the maximum available level of disagregation (173 components), for the period January

[6] For the US, we use the interval [0.05 : 0.70] due to the large weight of the component *Owner's equivalent rent of residence.*
[7] Base changes are treated in the same way as Rubio and Sansone (2015).

2002 to December 2019.

For the EA, we use the 93 seasonally adjusted components of the Harmonized Consumer Price Index, available in Eurostat for the same period.

For Colombia, we collect data from the National Department of Statistics (DANE). The dataset consists of 88 components for the period January 2009 to December 2018.[8]

For Peru, we collect CPI data for the Lima Metropolitan area published by the National Bureau of Statistics of Peru (INEI). The sample contains 54 CPI components from 2009 to 2019.

In order to summarize results, we will classify the components of each country into the six analytic categories: Durable manufactures (ManD), Non-durable manufactures (ManND), Services (SERV), Processed food (PF), Non-processed food (NPF), and Energy (ENE).

5.2 Results

In this section we report the results obtained for the five countries using the data and the framework previously described.

We organize the empirical evidence in four parts. First, we describe general findings that apply to all countries. Next, we include the evidence for the emerging markets (Chile, Colombia and Peru), and after that we include the results for the advanced economies (US and EA). Finally, we include a general discussion of the findings.

We report fully detailed results for Chile and, for the sake of brevity, only main results are reported for other countries and details are left to the appendix.

General findings

The most widely reported core measure by Central Banks excludes food and energy items (CPIXFE), because they are typically the most volatile.

The evidence shows that although the CPIXFE has lower volatility than headline inflation, it tends to be remarkably biased and only slightly persistent. In comparison with the other core measures, the CPIXFE is substantially more volatile, biased, and less persistent. Additionally, the CPIXFE tends to have low forecasting power, but this result is not general to all countries. Hence, as the CPIXFE ranks low in all of the dimensions considered. This result is independent of the weighting matrix used in the loss function.

Variable exclusion measures, such as TM, TMV, and our optimal fixed exclusion measure, OFE, tend to be among the best performers in terms of losses in all five countries, though their position in the ranking varies from case to case.

This finding leads us to conclude that the OFE is a relatively convenient indicator to be adopted as one of the main core measures by Central Banks. Despite being a fixed exclusion measure, it tends to be located close to the top of the ranking, far above the CPIXFE. Additionally, experience suggests that it is easier for Central Banks to communicate inflation measures that follow a fixed exclusion rule that can be revised periodically—say, every 5 years—than allowing variable trimming procedures that may look like blackboxes to the general public.

[8] A recent update of the base year of the CPI index took place in 2019. The update also changed the definitions of subcategories. The short sample prevented us from joining the old and new time series. We believe that one year of new data, i.e., for 2019, would not change our main results.

Emerging countries: Chile, Colombia, and Peru

Chile

First, we focus on the four relevant dimensions (persistence, volatility, bias, and forecasting error) of the core inflation measures. The left panel of Figure 2 depicts the value of the loss function for each of the core measures considered and the contributions of each dimension (ρ, σ, b, and $RMSFE$) to the loss. The table on the right reports the actual values of each dimension (scaled by 100) and, for completeness, losses are shown in the column on the right. Notice that rows are sorted in descending order according to the value of the loss.

The evidence in Figure 2 indicates that four of the measures perform well in terms of the loss: the trimmed means (TM and TMV), closely followed by the OFE, and the Median. Also, we find that the MAV is affected by a large bias. Headline CPI shows poor performance due to lack of persistence and large volatility and forecasting error.

The worst performer is the CPIXFE, which scores the largest loss, even larger than the CPI itself. An important driver of the bad performance of the CPIXFE is its large bias. Nonetheless, the CPIXFE is the worst core measure in every individual dimension, which means that its position on the ranking is independent of the weighting matrix used to compute the loss.

Notice that for the Chilean case only, we decided to use the inflation target as benchmark (μ_0) to measure bias. The average YoY CPI inflation from January 2003 to December 2019 is 3.1% very close to the announced 3% target.[9]

Figure A.2 in Appendix A illustrates the values of the loss function for all of the parameters considered in the construction of the TM (left panel) and TMV (right panel). An important conclusion is that the optimal choice of trimming parameters is substantially higher than the calibrated value of 15%, that is widely used in the literature on developed economies.

We now turn to a detailed analysis of the excluded components, since we are interested in assessing whether the trimmed items make sense from an economic point of view. For the purpose of organizing the analysis, we will classify the 144 components into the six categories described in §5.1. We focus first on the variable exclusion measures (TM, and TMV) and then on the OFE.

Figure 3 describes the proportion of the total weight of each category that is trimmed at each point in time by the TM (left panel) and the TMV (right panel). In both cases, a high trimming rate is obtained for the categories energy and non-processed food, which contrasts with the low trimming rate for services. In those three categories, the trimming rates are more stable than in the three remaining ones.

The figure highlights two reasons that make the usual practice of excluding only food and energy to be inadequate: (i) In the case of Chile, the CPIXFE reported by the National Bureau of Statistics (INE) excludes both unprocessed and processed food. Results in Figure 3 indicate that although the permanent exclusion of unprocessed food seems justified, excluding processed food is not. In fact, since 2012, processed food is, after services, the least trimmed category. (ii) In both figures we observe that although the maximum trimming is done in the energy and unprocessed food categories, the rest of the categories also show relevant trimming. The case of non-durable manufactures stands out, showing a high and increasing level of trimming since 2011.

In summary, optimal trimming methods tend to exclude almost all components of *energy* and *unprocessed food*,

[9] Changing the benchmark to the actual mean of the YoY CPI does not change the main results. Details are available upon request.

but relevant proportions of other categories are also excluded, among which we highlight *manufactured durables*. In addition, since 2012, *processed food* is the second category with lower trimming after *services*. Thus, we can conclude that the usual practice of excluding food and energy does not seem justified from an empirical point of view for the Chilean case.

Another way to analyze this same evidence is by plotting the proportion of the time (months) each component is trimmed. Figure 4 does this for the TMV, assigning the same color to all of the components in the same category (as the conclusions do not change, the plot corresponding to the TM is included in appendix A).

Each bar of the figure represents a component, and, unlike Figure 3, the weights are not taken into account (the specific names of the subcategories corresponding to each of the bars of the graph are included in Table A.1 of Appendix A). The results confirm previous findings: Components that are less likely to be excluded belong, in general, to *services*, which appear to be concentrated on the left-hand side of the plot. However, three specific services whose costs are defined by external variables tend to be highly volatile and, therefore, frequently excluded: *road passenger transport services*, *passenger air transport services*, and *all-inclusive travel services*. It is noteworthy that monetary policy reports of the Central Bank of Chile have usually highlighted those items for causing abnormal headline inflation behavior[10].

Apart from the services listed above, the components of *energy* and *non-processed food*, some items in the category *durable manufactures* also suffer large trimming. This is explained by the fact that most durable manufactures are imported and their price variations are strongly associated with movements of the exchange rate, as well as usual sales at retail stores.

Interestingly, the fixed exclusion measure, OFE, preserves the trimming structure of the variable exclusion measures. Comparing the trimming proportions of the OFE and the CPIXFE, both measures trim high proportions of energy and non-processed food, as Figure 5 shows. However, the CPIXFE excludes components that should be maintained (processed food) and keeps others that should be trimmed (durable manufactures).

To close the analysis for Chile, Figure 6 presents the YoY variation of the seven indicators under analysis as well as the inflation target of Chile, which has been in effect since September 2001. Casual observation suggests a broad comovement among the indicators. In particular, *CPIXFE* comoves in direction and magnitude with the *CPI* in events in which inflation significantly falls. However, in episodes in which inflation accelerates, this comovement breaks down, due to increases in the relative prices of food and energy. The episode before the Subprime crisis is a good example of the mentioned pattern. The other core measures (those constructed using our proposed strategy), seem to reflect the low frequency movements of the CPI while smoothing out the noise.

Colombia

Figure 7 presents the main results (as stated at the beginning of this section, detailed results are included in Appendix A).

The evidence confirms that variable trimming measures are among the best performers, since they yield the lowest losses. As was the case for Chile, despite being a fixed exclusion measure, the OFE is very close to the TM and TMV. On the other hand, the Median, CPIXFE, and MAV show the highest values of the loss function—even

[10] See, e.g., the Monetary Policy Report of September 2019 (available in Spanish, we translate the sentence into English): "In contrast, inflation of goods was somewhat higher than expected, but largely explained by all-inclusive travel services that shows high historical volatility, which is supposed to be reversed for the near future". The explicit mention suggests that a temporary supply shock is responsible of the significant rise in juncture inflation. See www.bcentral.cl/en/content/-/details/banco-central-publico-informe-de-politica-monetaria-ipom-de-septiembre-de-2019-6.

larger than that of the CPI, mainly due to large biases.[11]

Large bias in median inflation is surprising. A plausible explanation point to the choice of μ_0 we used as the benchmark (mean MoM CPI inflation over the sample Jan-2009 to Dec-2018). Recent macroeconomic history of Colombia shows that during 2015-2016, the exchange rate has been subject to large depreciation as a consequence of important external shocks (such as the oil price shock). Additionally, there was a big increase in food prices driven by the *El Niño* phenomenon. These supply shocks were large, had second-round effects, and were absorbed with a surge of inflation. However, as the upsurge in inflation was mainly focused on energy and non-processed food, it could be the case that the weighted median was not affected.

The fact that the OFE still performs well in this case reinforces the argument that our methodology is flexible and robust enough to treat volatile inflation data coming from emerging and small open economies, that are exposed to large supply and terms of trade shocks, such as Chile and Colombia.

For further details on this application, see Figure A.6 in Appendix A.

Peru

As noted in §5.1, for Peru we have only 53 components. Thus, this case constitutes an example of how our proposal behaves in situations with a small number of components.

Results are reported in Figure 8. As was the case fpr Chile and Colombia, the CPIXFE is among the worst performers (in this case it is the worst). Again, its position in the ranking does not depend on the weighting matrix, since it shows bad results in every dimension.

Our exclusion measures are the top performers, with the fixed exclusion measure, OFE, begin the second best after the TMV. One takeaway of this application is that our procedure seems to remain robust when the number of components is small. For further details on this application, see Figure A.7 in Appendix A.

Advanced economies: US and Euro Area

US

Figure 9 includes the main results for the US. The general conclusions of previous applications are still valid for this case. Namely, the best performers are our variable exclusion measures, followed by the OFE; the CPIXFE appears as the worst performer. Compared with the the OFE, the CPIXFE is less persistent, marginally more volatile, remarkably more biased, and has a slightly higher forecasting power.

It is noteworthy that the unusual high weight of the component *Owner's equivalent rent of residence* in the US CPI (25% approximately) may imply that the trimming parameters change abruptly from month to month, depending on whether this component is trimmed. We examined how the procedure performs when excluding this component from the analysis, and the main conclusions remain valid (details available upon request).

Euro Area

Results in Figure 10 confirm the poor performance of the CPIXFE: It is less persistent, more volatile, more biased, and has less forecasting power than measures constructed using the loss function. This means, once again, that its low position in the ranking does not depend on the specific weighting matrix we are using.

The OFE is at the top of the ranking, outperforming the variable exclusion measures. This result is mainly explained by the somehow larger persistence of the OFE in comparison with the variable exclusion measures. More

[11] Note that a bias of the CPI may differ from zero because the evaluation period does not include the full sample, since we reserve the end of the sample to evaluate the forecasts.

detailed results are included in Figure A.5 of Appendix A.

5.3 Discussion

Our results show that the core measures constructed by optimizing the loss function are situated at the top of a ranking constructed using the same loss function. Naturally, this should not be a surprise.

What our results do highlight is that there is a simple way to do, in a systematic, objective, and accountable way, what Central Banks usually do in an adhoc and sometimes misguided fashion. As the applications for the five countries show, improvements in the quality of core measures can be substantial.

Consider, for example, the usual practice of excluding food and energy. Since these components are among the most volatile, it is common in Central Banks to use the CPI excluding them (CPIXFE) as their core measure of reference. Our results show that this is a misguided practice, as the CPIXFE has quite poor statistical properties. It is biased, volatile, and has low persistence and low forecasting power. In some cases the headline CPI itself is a better core indicator than the CPIXFE. We propose a simple way of solving the CPIXFE's drawbacks, which consists of optimally choosing the (possibly fixed) components to exclude.

We treated the loss function agnostically, as we placed equal weights on the four dimensions considered. These weights can be changed to accommodate alternative preferences of the policymakers.

Finally, a comment about not considering the correlation between the core measure and the output gap as a relevant dimension is in order. We made this decision to avoid entering into country-specific discussions about the (in)validity of the Phillips curve, given the heterogeneity of controls to choose, issues with expectations, and other endogeneity issues. Still, we included this dimension for the Chilean case, and the main conclusions do not change (details available upon request).

6 Conclusions

We argue that caution is warranted in constructing core inflation measures. The problem is that by excluding volatile components—or those that have shown large forecast errors in the recent past—one may end up analyzing an indicator with undesirable statistical properties. This is the case for the usual measure that excludes food and energy from the CPI, which tends to be biased, volatile, only slightly persistent, and a bad indicator for forecasting the CPI.

We proposed a systematic and objective methodology for choosing which components to exclude. Our proposal consists of selecting the components based on a loss function that looks for an optimal balance between four statistical dimensions (volatility, persistence, bias, and forecasting power). The exclusion may be variable (excluded items change from month to month) or fixed. Adding more dimensions to the function is trivial.

Our empirical evidence clearly shows that by optimally selecting the components to be excluded, properties of core inflation measures can be substantially improved. In addition to improving the statistical properties of the resulting measure, our strategy also leads to exclusions that make sense from an economic point of view. This validation stage confirms that the method tends to exclude energy and non-processed food items while retaining services. For the case of durable and non-durable manufactures and processed food, the proportions of excluded components vary from country to country.

A usual justification for the use of adhoc exclusion criteria is that they are simple to communicate because they always exclude the same items. Since our strategy allows the exclusion to be fixed, we can achieve the same objective. Hence, nothing is lost and much can be gained by optimally selecting the excluded items instead of sticking with the usual adhoc criteria.

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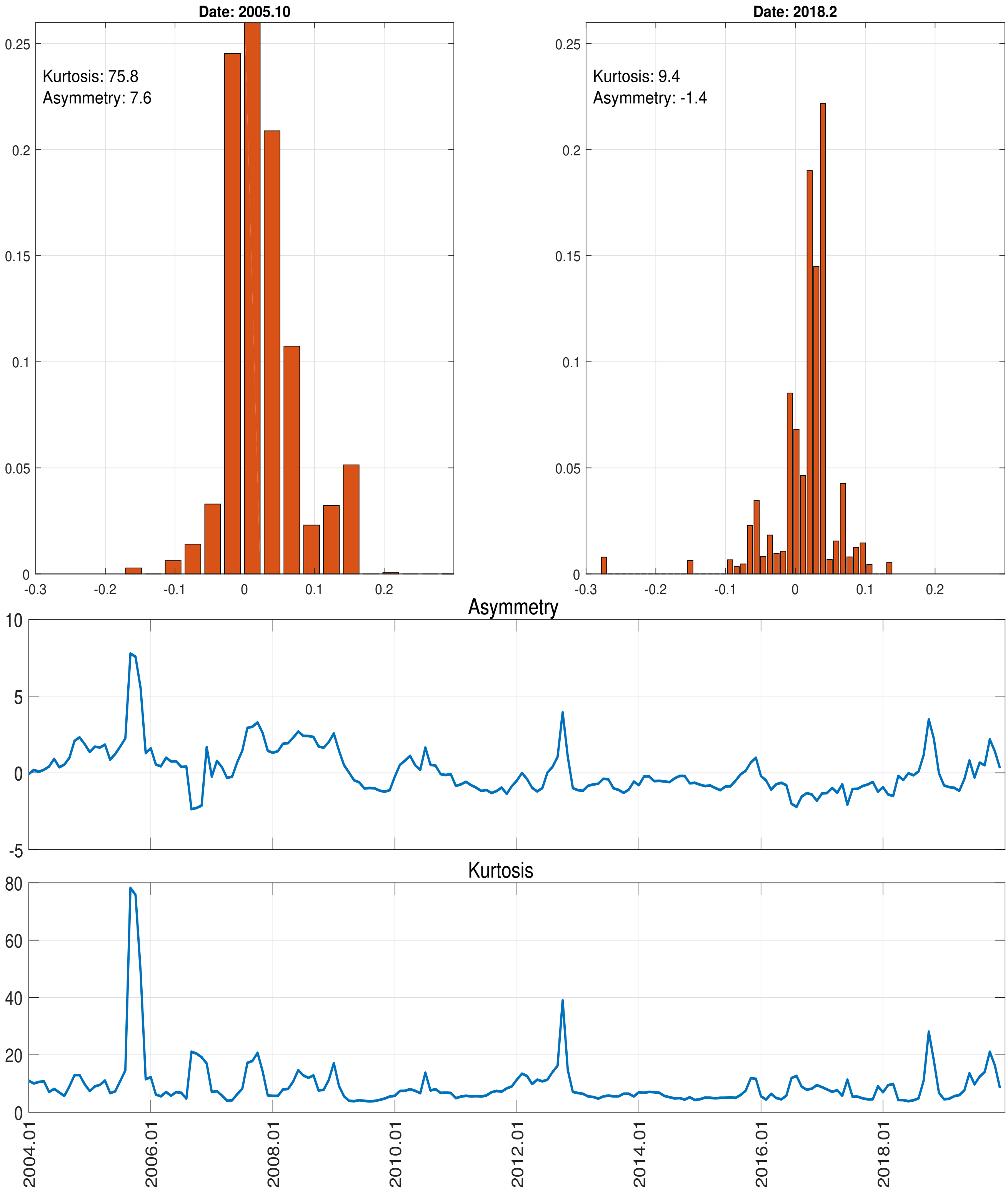
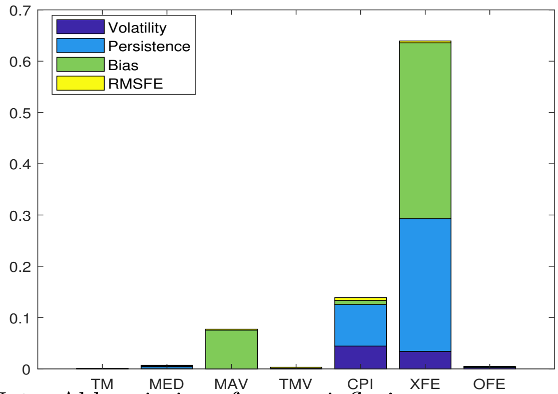
Figure 1: Cross-sectional distributions of the annual variation of CPI components in the US



Note: Examples of the full distributions at two points in time (first two upper graphs) and the the third and fourth moments in the whole sample (bottom two graphs).

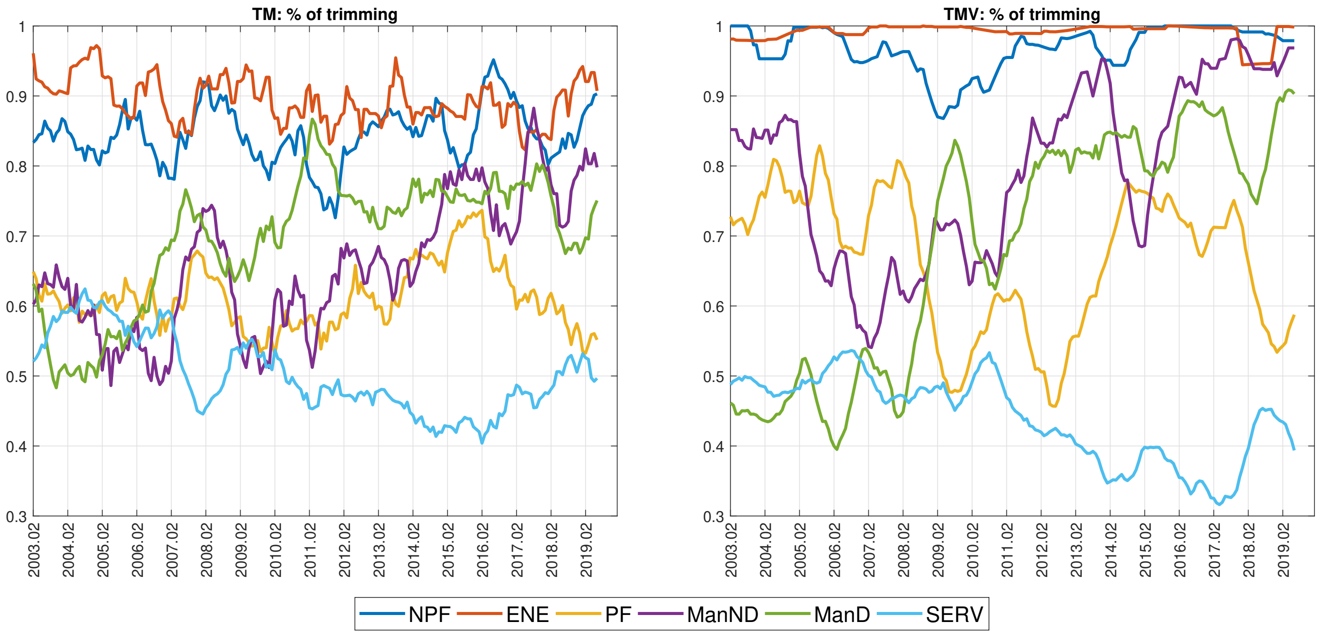
Figure 2: Details of the loss function for Chile



	ρ	σ	$\mu - \mu_0$	RMSFE	L
TM	0.74	0.10	0.01	0.35	0.08
TMV	0.72	0.09	0.03	0.37	0.32
OFE	0.70	0.14	0.03	0.33	0.49
MED	0.68	0.11	0.04	0.37	0.71
MAV	0.74	0.09	0.27	0.37	7.74
CPI	0.46	0.30	0.09	0.40	13.90
XFE	0.23	0.27	-0.59	0.39	63.94

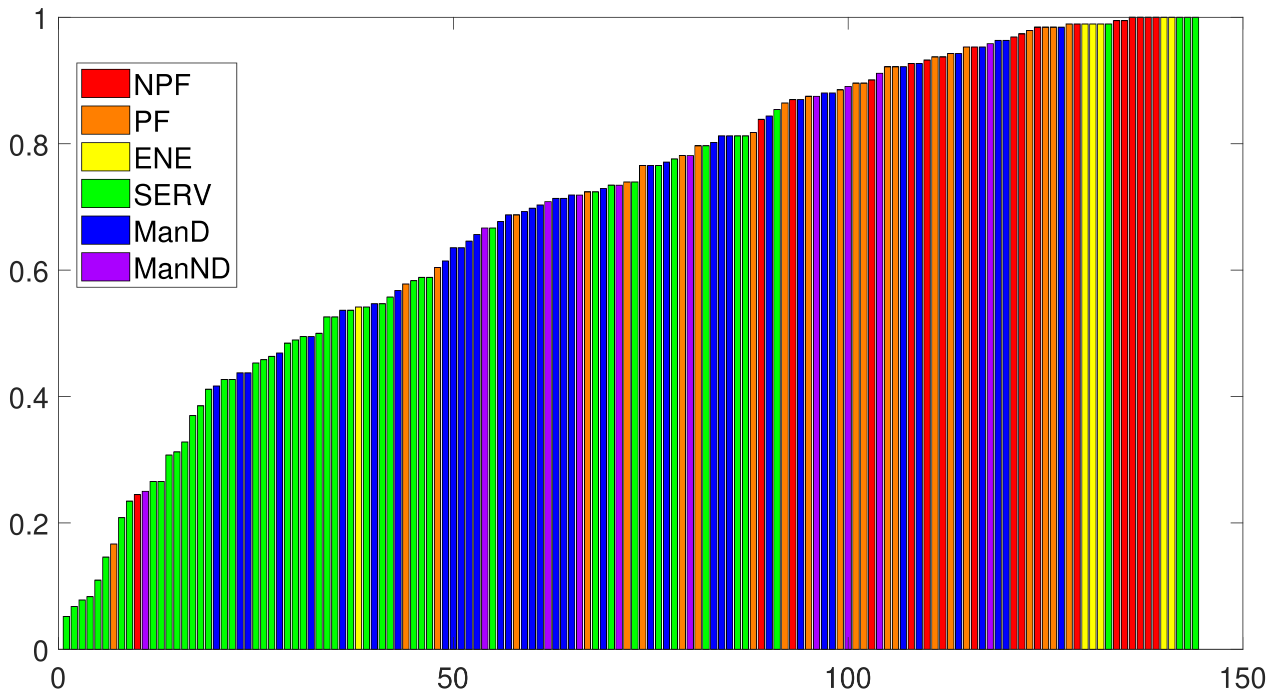
Note: Abbreviations for core inflation measures are defined in Table 1. ρ denotes persistence; σ volatility; $\mu - \mu_0$ bias; $RMSFE$ stands for root mean squared forecasting error; and L stands for the value of the loss function (scaled by 100 in the table). For details see §4.2.

Figure 3: Proportion of the trimmed weight in each category (centered 12-month moving average)



Note: Abbreviations: NPF, non-processed food; PF, processed food; ENE, energ; SERV, services; ManD, manufactured durables; ManND manufactured non-durables.

Figure 4: Components' trimming frequency (TMV)



Note: Abbreviations: NPF, non-processed food; PF, processed food; ENE, energ; SERV, services; ManD, manufactured durables; ManND manufactured non-durables.

Figure 5: Chile: Trimming proportions by category: OFE and CPIXFE

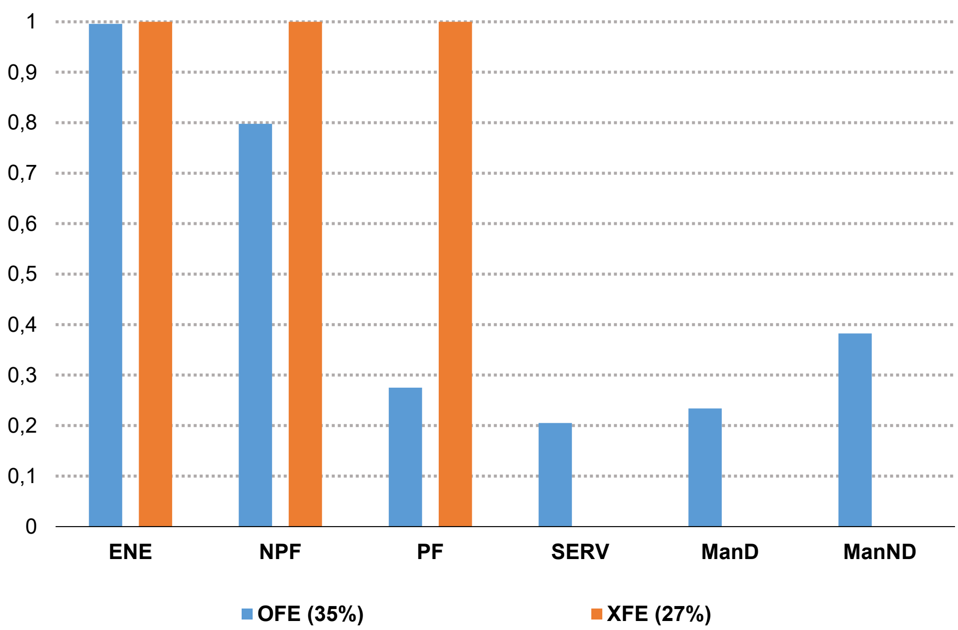
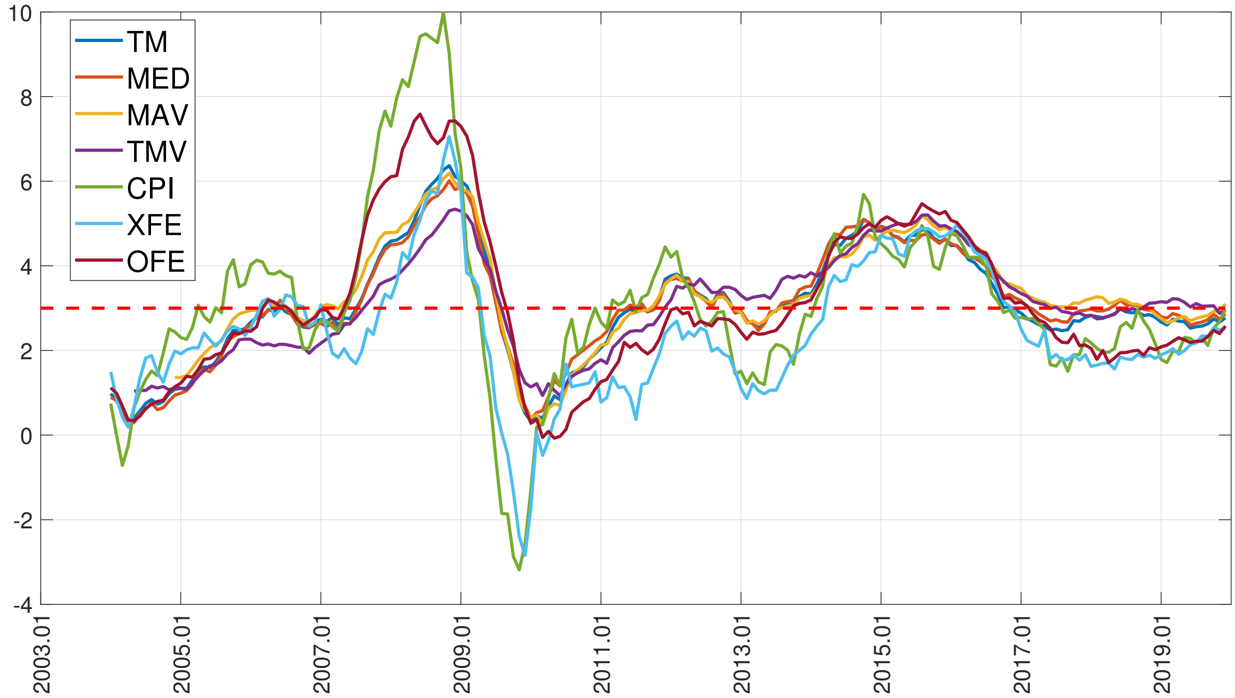
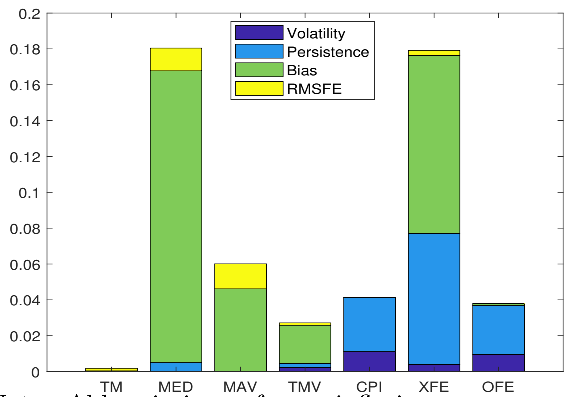


Figure 6: Core inflation measures, YoY variation (percentages)



Note: Red dashed line denotes the inflation target (3%). For abbreviations, see note of Figure 3.

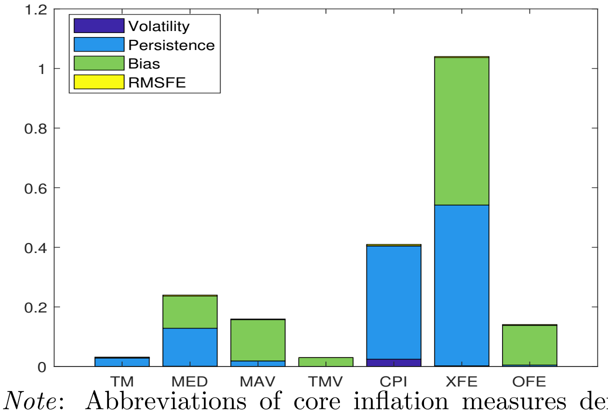
Figure 7: Details of the loss function for Colombia



	ρ	σ	$\mu - \mu_0$	RMSFE	L
TM	0.77	0.07	0.00	0.79	0.19
TMV	0.75	0.10	-0.15	0.82	2.84
OFE	0.67	0.13	-0.13	0.76	3.73
CPI	0.63	0.16	0.01	0.80	3.86
MAV	0.79	0.05	-0.21	0.91	6.62
XFE	0.53	0.11	-0.31	0.84	17.58
MED	0.73	0.06	-0.40	0.90	18.49

Note: Abbreviations of core inflation measures defined in Table 1. ρ denotes persistence, σ volatility, $\mu - \mu_0$ bias, and $RMSFE$ stands for root mean squared forecasting error, L stands for the value of the loss function (scaled by 100 in the table), for details see §4.2.

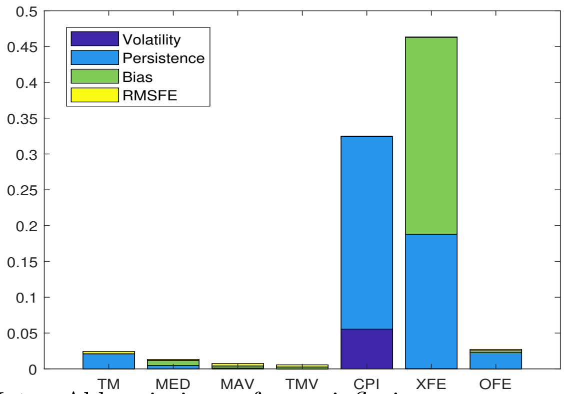
Figure 8: Details of the loss function for Peru



	ρ	σ	$\mu-\mu_0$	RMSFE	L
TMV	0.05	0.77	-0.17	0.26	0.03
TM	0.07	0.6	0.01	0.31	0.03
OFE	0.06	0.7	-0.37	0.31	0.14
MAV	0.06	0.63	-0.37	0.31	0.16
MED	0.08	0.41	-0.33	0.32	0.24
CPI	0.21	0.15	0.03	0.33	0.41
XFE	0.1	0.03	-0.7	0.32	1.04

Note: Abbreviations of core inflation measures defined in Table 1. ρ denotes persistence, σ volatility, $\mu - \mu_0$ bias, and $RMSFE$ stands for root mean squared forecasting error, L stands for the value of the loss function, for details see §4.2.

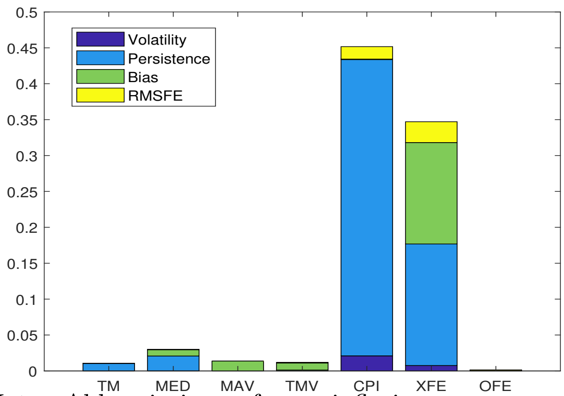
Figure 9: Results for US



	ρ	σ	$\mu-\mu_0$	RMSFE	L
MAV	0.80	0.04	0.01	0.40	0.01
TMV	0.75	0.04	-0.03	0.39	0.26
MED	0.77	0.05	-0.08	0.43	0.78
TM	0.68	0.05	-0.01	0.45	1.32
OFE	0.69	0.04	0.05	0.44	1.47
CPI	0.32	0.28	0.01	0.40	28.40
XFE	0.40	0.06	-0.52	0.42	42.92

Note: Abbreviations of core inflation measures defined in Table 1. ρ denotes persistence; σ volatility; $\mu - \mu_0$ bias; $RMSFE$ stands for root mean squared forecasting error;and L stands for the value of the loss function (scaled by 100 in the table). For details, see §4.2.

Figure 10: Results for the Euro Area



	ρ	σ	$\mu-\mu_0$	RMSFE	L
OFE	0.83	0.04	-0.01	0.41	0.00
TM	0.73	0.04	-0.01	0.39	0.01
TMV	0.80	0.03	-0.10	0.41	0.01
MAV	0.84	0.02	-0.12	0.38	0.01
MED	0.69	0.04	-0.09	0.40	0.03
XFE	0.43	0.11	-0.38	0.55	0.32
CPI	0.20	0.17	-0.02	0.51	0.43

Note: Abbreviations of core inflation measures defined in Table 1. ρ denotes persistence; σ volatility; $\mu - \mu_0$ bias; $RMSFE$ stands for root mean squared forecasting error; and L stands for the value of the loss function. For details, see §4.2.

Table 1: Summary of core inflation measures

Measure	Abbreviation	Param. to choose	Fixed excl.
CPI without food and energy	*CPIXFE*	—	Yes
Median inflation	*Median*	—	No
Trimmed mean	*TM*	α_0, α_1	No
Trimmed mean by variance	*TMV*	α, h	No
Mean adjusted by variance	*MAV*	h	No
Optimal fixed exclusion	*OFE*	α_0, α_1	Yes

Table 2: Algorithm for core inflation measures.

Core Inflation Abbrev.	Trimmed Mean TM	Trimmed Mean by Volatility TMV	Mean adjusted by Variance MAV	Optimal Fixed Exclusion Index OFE	Median MED
Step 1	Define a vector with a grid for parameters α_0 and α_1.	Define a vector with a grid for parameters α and h.	Compute w^{mav} of Equation (3)	Compute σ for each component and sort them from lowest to largest σ	Calculate π_{it}
Step 2	Construct all possible trimmed means for the grid α_0, α_1.	Construct all possible trimmed means for the grid α and h.	Construct $(\pi_{t,h}^{MAV})$ as in Equation (3), for the grid $h = \{6, 12, 18, 24\}$.	Aggregating the components in the order determined in step 1, construct aggregates (p_j) that represent between 10% and 90% of the CPI's weight.	Determine the weighted median element inflation for each period.
Step 3	Compute the statistics defined in §4.1 and set the benchmarks as in Equation (9)				—
Step 4	Evaluate loss functions (L) for each TM (step 2) and take the one with the lowest L, which is denoted π_t^{TM}	Evaluate L for each TMV (step 2) and take the one with the lowest L, which is denoted π_t^{TMV}.	Evaluate L for each MAV (step 2) and take the one with the lowest L, which is denoted π_t^{MAV}.	Evaluate L for each p_j (step 2) and take the one with the lowest L, which is denoted π_t^{OFE}.	Construct the series π_t^{MED}.
Step 5	For each Core CPI series described above, as well as XFE and CPI, indexed by j, calculate μ_j, ρ_j, σ_J and $RMSFE_j$				
Step 6	Considering all the constructed core measures plus XFE and CPI, set the benchmarks as in Equation (9)				
Step 7	Evaluate $L(j)$ for each of the inflation measures and order them from low to high loss.				

A Additional figures

Figure A.1: Kurtosis and asymmetry coefficients for selected countries.

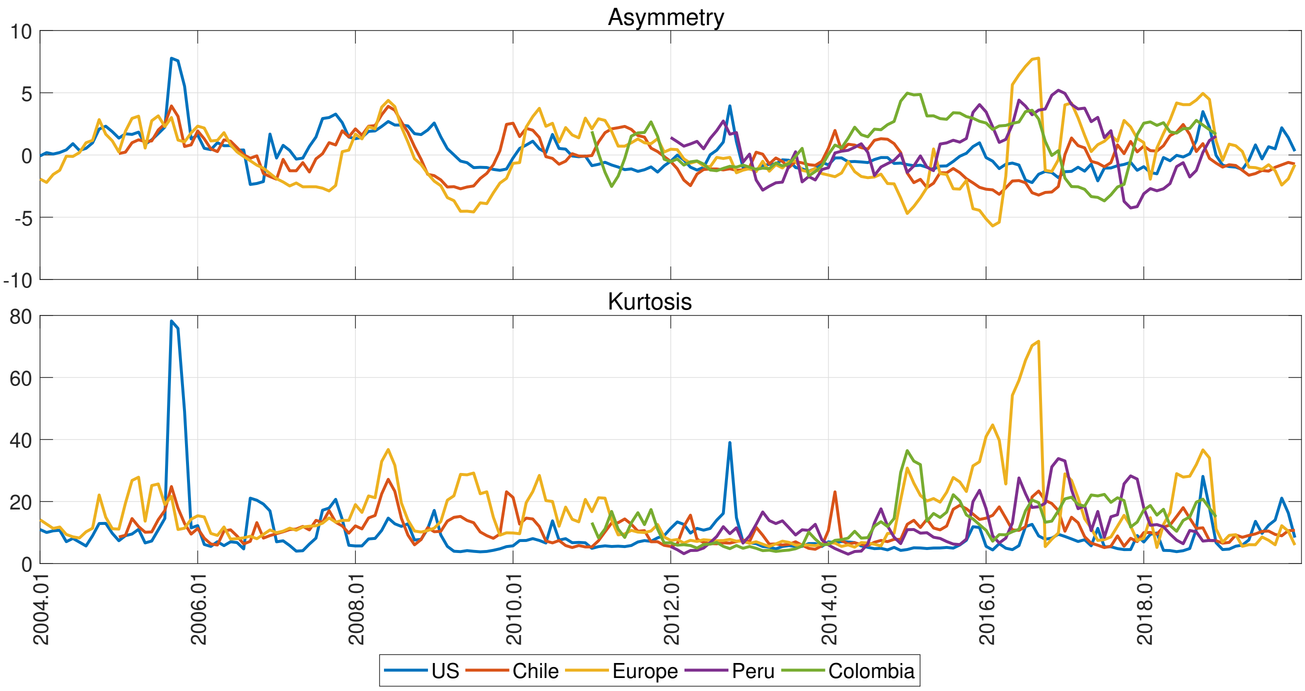
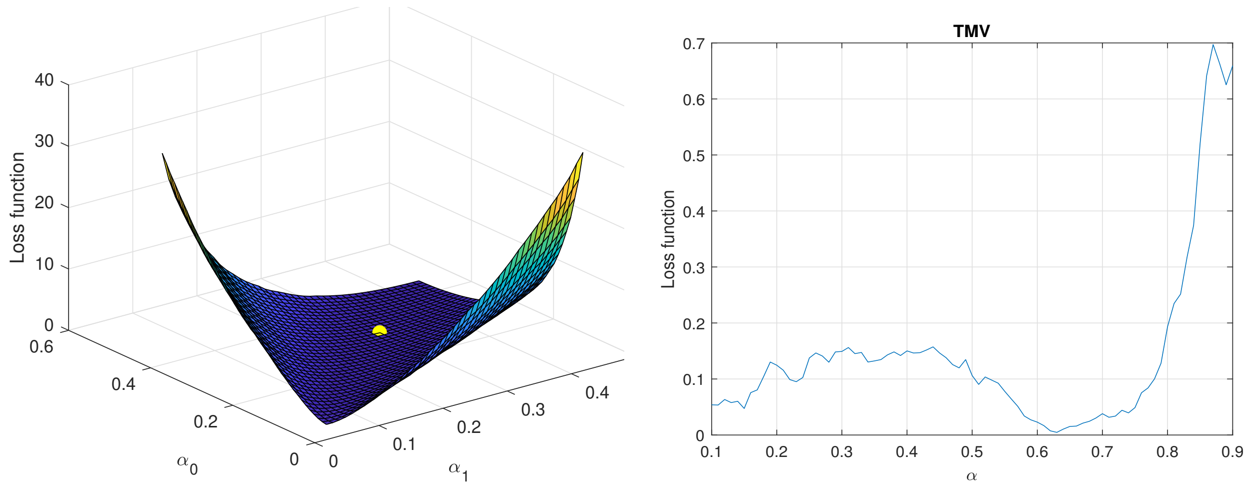
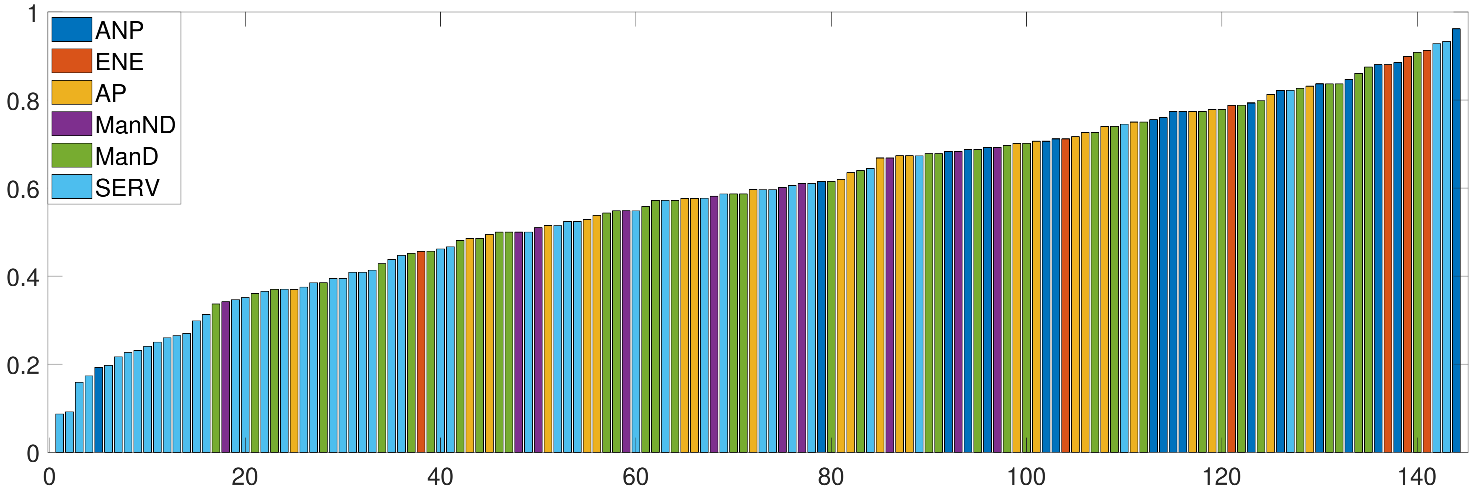


Figure A.2: Loss function for the TM (left panel) and TMV (right panel) for all trimming parameters considered.



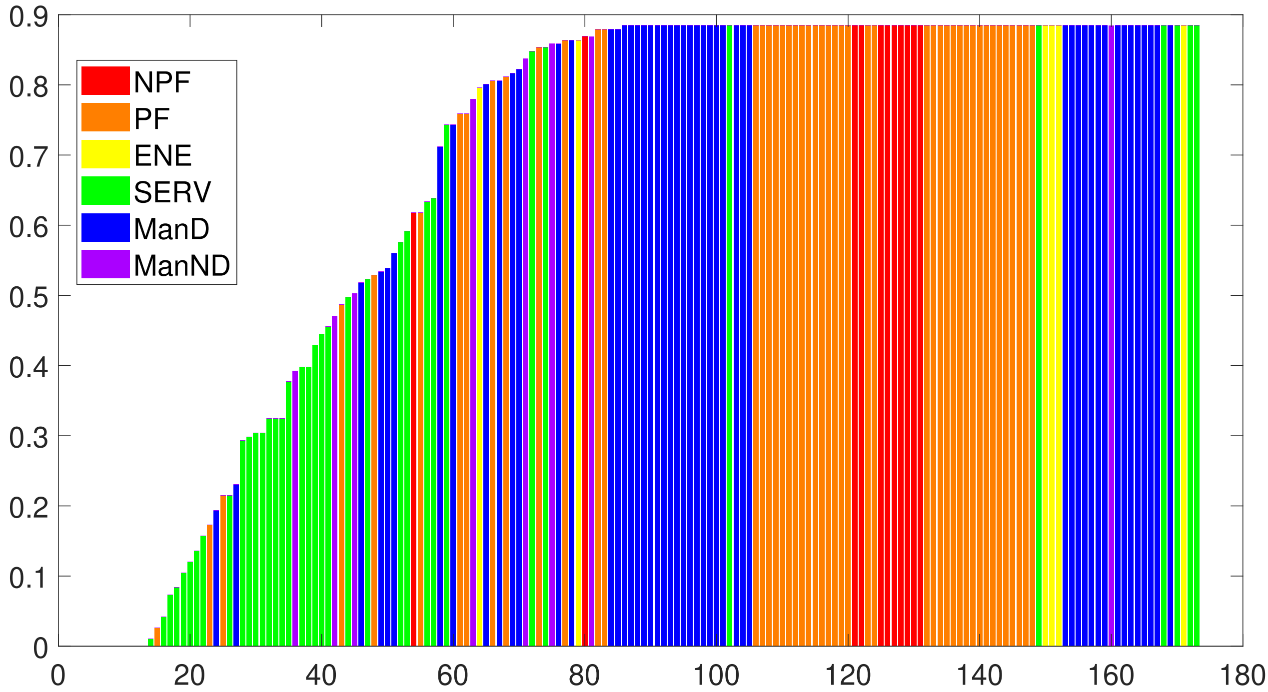
Note: Relevant parameters to calculate TM and TMV measures are defined in Table 1.

Figure A.3: Chile: Share of the time in which each subcategory is trimmed (TM).



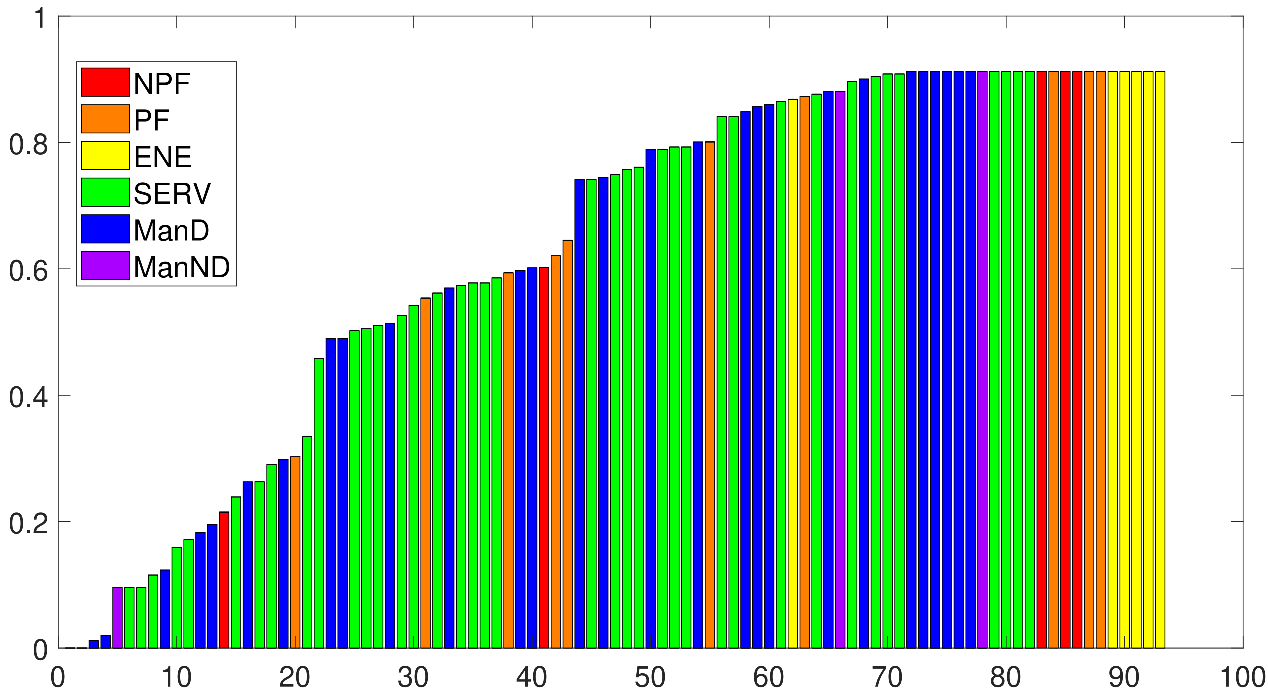
Note: For abbreviations, see note of Figure 3.

Figure A.4: US: Components' trimming frequency (TMV)



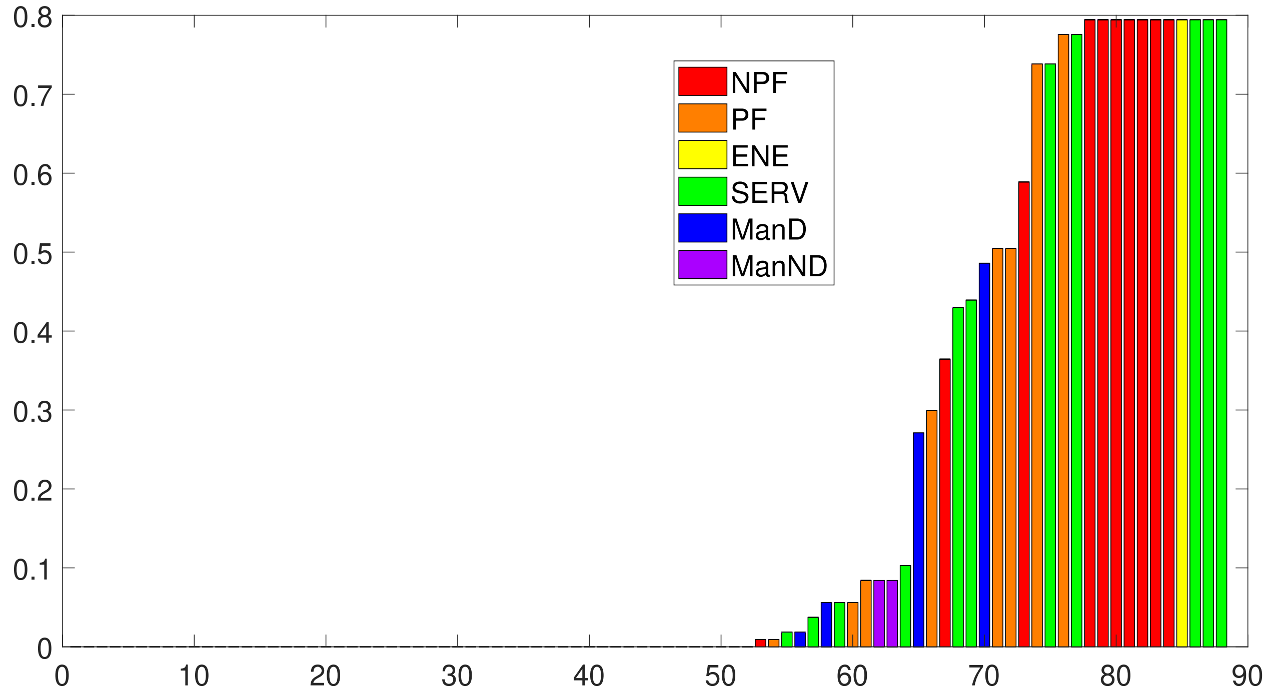
Note: For abbreviations, see note of Figure 3.

Figure A.5: EU: Components' trimming frequency (TMV)



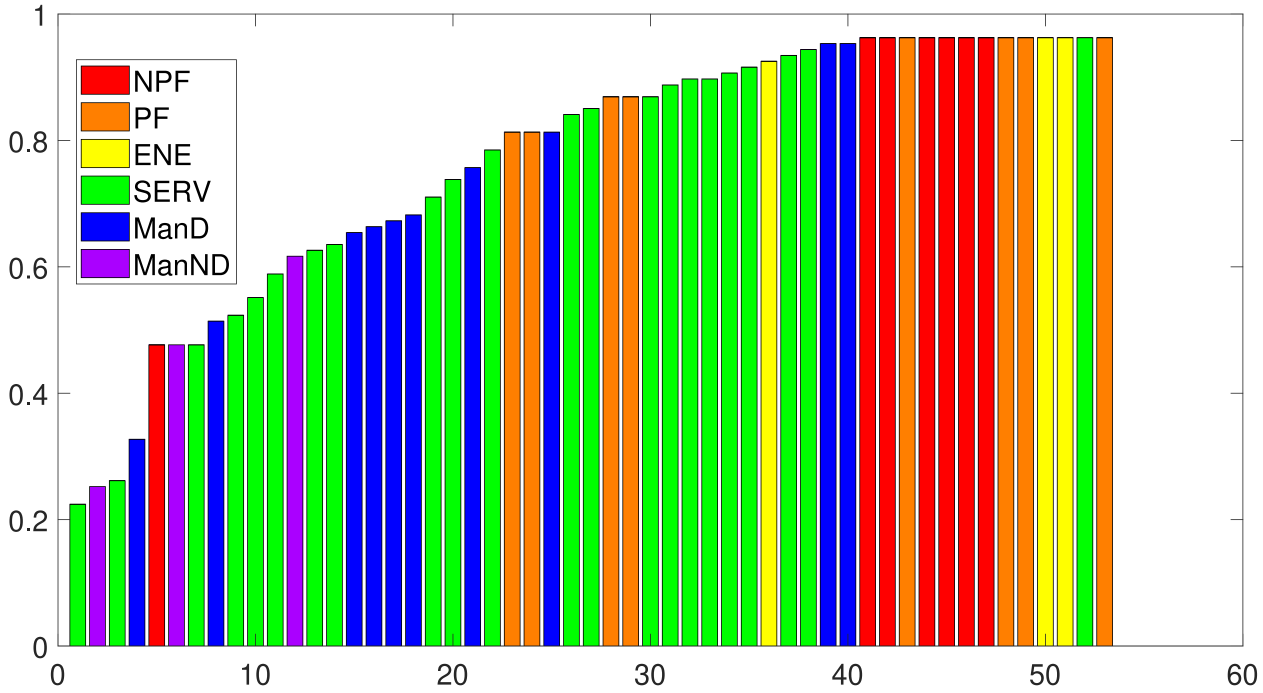
Note: For abbreviations, see note of Figure 3.

Figure A.6: Colombia: Components' trimming frequency (TMV)



Note: For abbreviations, see note of Figure 3.

Figure A.7: Peru: Components' trimming frequency (TMV)



Note: For abbreviations, see note of Figure 3.

Table A.1: Details of Figure 4

	Subclass	Category	% time
1	Home lease	SERV	0.05
2	Medical and paramedical services	SERV	0.06
3	Domestic Services	SERV	0.09
4	Other telecomunnication services	SERV	0.09
5	Pre-school and primary education services	SERV	0.09
6	High-school education services	SERV	0.12
7	Food and drinks consumed away from home	PF	0.16
8	Lamb meet and others	NPF	0.21
9	Dental services	SERV	0.22
10	Higher education services	SERV	0.23
11	Newspapers	ManND	0.24
12	Services of other health professionals	SERV	0.25
13	Medical services	SERV	0.27
14	Laboratory medical analysis services, diagnostic and radiological services	SERV	0.27
15	Gambling and related	SERV	0.27
16	Hospitalization services	SERV	0.31
17	Hairdressind and personal care services	SERV	0.34
18	Co-owner home expenses	SERV	0.34
19	Other housing-related services	SERV	0.39
20	Books	ManD	0.41
21	Footwear repair services	SERV	0.43
22	Services related to the circulation of vehicles	SERV	0.43
23	Desktop items	ManD	0.43
24	School wardrobe items	ManD	0.44
25	Home furnishing	ManD	0.45
26	Veterinary services	SERV	0.45
27	Clothing cleaning and repair services	SERV	0.46
28	Post services	SERV	0.46
29	School supplies	ManD	0.46
30	Motorcycle	ManD	0.46
31	Other services	SERV	0.47
32	Pre-university services	SERV	0.48
33	Garbage removal services	SERV	0.50
34	Lubricants and oils for the automobile	ENE	0.50
35	Car maintenance and repair services	SERV	0.51
36	Telecommunications services	SERV	0.51
37	School texts	ManD	0.53
38	Ambulance services	SERV	0.54
39	Bicycle	ManD	0.54
40	Household items and utensils	ManD	0.54
41	Home conservation and repair services	SERV	0.56
42	Sports and recreational classes	SERV	0.56
43	White line	ManD	0.57
44	Passenger transportation services by urban roads	SERV	0.58
45	Educational services not attributable to any level	SERV	0.58
46	Parking services	SERV	0.58
47	Household accesories	ManD	0.59
48	TV services	SERV	0.59
49	Materials for the conservation and repair of the house	ManD	0.61
50	Appliances and white line repair services	SERV	0.61
51	Bread and other backery products	PF	0.61
52	Women's costume	ManD	0.61
53	Passenger transportation services by rail	SERV	0.61
54	Jewelry and watches	ManD	0.63
55	Powder and liquid juices	PF	0.63
56	Household cleaning products	ManND	0.63
57	Men's costume	ManD	0.64
58	Clothing items and accesories	ManD	0.64
59	Home appliances	ManD	0.65
60	Tools	ManD	0.65
61	Video game toys and consoles	ManD	0.65
62	Household cleaning items	ManND	0.66
63	Home textiles	ManD	0.67
64	Children's costume	ManD	0.69
65	Beberages	PF	0.70
66	Transportation-related insurance	SERV	0.70
67	Personal hygiene products	ManND	0.70
68	Hotels and accomodation services	SERV	0.71
69	Furniture repair service	SERV	0.71
70	Foods ready to go	PF	0.71

Table A.2: continuation of Table A.1

	SubClase	Catagoría	% Tiempo
71	Sports, camping and recreation equipment	ManD	0.72
72	Beauty products	ManND	0.72
73	Fabrics for producing apparel	ManD	0.72
74	Articles and ornamentation for home	ManD	0.74
75	Other medical products	ManND	0.74
76	New car	ManD	0.75
77	Soups and creams, baby foods and non-dairy deserts	PF	0.75
78	Yogurts and dairy desserts	PF	0.77
79	Distilled beberages	PF	0.77
80	Water and sewerage supplies	SERV	0.77
81	Passenger combined transport services	SERV	0.77
82	Sound and picture records	SERV	0.78
83	Artifacts and therapeutic items	ManD	0.79
84	Beers	PF	0.79
85	Services provided by recreation and sports clubs	SERV	0.80
86	Photo services	SERV	0.80
87	Cigarettes	PF	0.82
88	Audio equipment	ManD	0.82
89	Milk	NPF	0.83
90	Used car	ManD	0.83
91	Candies, chocolates and other confectionery products	PF	0.84
92	Expenses in administration of financial services	SERV	0.84
93	Sugar and sweeteners	PF	0.85
94	Gardening and flowers	ManND	0.85
95	Men's footwear	ManD	0.86
96	Dry fruits and canned fruits	PF	0.87
97	Mineral and purified water	NPF	0.87
98	Personal care products	ManND	0.87
99	Food and accessories for pets	ManND	0.88
100	Other personal items	ManD	0.88
101	Sauces and dressings	PF	0.88
102	Salt, herbs, spices and culinary condiments	NPF	0.89
103	Canned fish and seafood	PF	0.89
104	Cameras	ManD	0.89
105	Infant clothing	ManD	0.90
106	Pasta	PF	0.90
107	Tee	NPF	0.91
108	Wine	PF	0.91
109	Telephone equipment	ManD	0.91
110	Ice cream	PF	0.92
111	Television	ManD	0.92
112	Flours and cereals	NPF	0.93
113	Jam, other jelly spreads	PF	0.93
114	Coffee and substitutes	NPF	0.93
115	Cocoa in powder	NPF	0.94
116	Computers and printers	ManD	0.94
117	Butter and margarine	PF	0.94
118	Spare parts and accessories for the car	ManD	0.94
119	Cheese	PF	0.95
120	Medicines	ManND	0.95
121	Fresh, refrigerated or frozen poultry	NPF	0.96
122	Fresh, refrigerated or frozen seafood	NPF	0.96
123	Women's footwear	ManD	0.96
124	Services provided by cultural establishments	SERV	0.96
125	Processed meat and cold meats	PF	0.96
126	Edible oils	PF	0.96
127	Fresh, refrigerated or frozen beef	NPF	0.97
128	Children's footwear	ManD	0.97
129	Eggs	PF	0.97
130	Electricity	ENE	0.97
131	Gas (network)	ENE	0.97
132	Other household fuels	ENE	0.97
133	Rice	NPF	0.98
134	Fresh, refrigerated or frozen pork meat	NPF	0.98
135	Fresh, refrigerated or frozen fruits	NPF	0.98
136	Fresh, refrigerated or frozen fish	NPF	0.98
137	Fresh, refrigerated, frozen or preserved vegetables	NPF	0.98
138	Legumes and dried vegetables	NPF	0.98
139	Tuberns and derivative products	NPF	0.98
140	Liquid gas	ENE	0.98
141	Fuels for the car	ENE	0.98
142	Road Passenger transportation services	SERV	0.98
143	Passenger transportation services by air	SERV	0.98
144	All-inclusive travel services	SERV	0.98

Table A.3: OFE trimmed categories by type

	Chile		US		EA		Colombia		Peru	
	N	W	N	W	N	W	N	W	N	W
NPF	6	0.016	0	0.000	2	0.058	8	0.102	1	0.056
PF	17	0.152	2	0.006	0	0.000	15	0.179	0	0.000
ENE	1	0.000	1	0.008	0	0.000	1	0.009	0	0.000
SERV	30	0.326	23	0.504	9	0.206	26	0.452	5	0.178
ManD	28	0.112	2	0.044	6	0.059	25	0.161	6	0.089
ManND	7	0.044	0	0.000	1	0.009	11	0.083	3	0.086
Total	89	0.650	28	0.562	18	0.332	86	0.986	15	0.409

Note: Abbreviations: NPF, non-processed food; PF, processed food; ENE, energ; SERV, services; ManD, manufactured durables; ManND manufactured non-durables.