The determinants of inflation volatility: a panel data analysis for US- product categories

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Abstract

Some macroeconomic dimensions like the economic business cycle, the exchange rate movements when the degree of country openness is significant, or the level of inflation are often considered to explain measured-inflation dynamics. However, inflation volatility may also be affected by statistical agencies methodological changes. This paper explores both potential explanations in a panel data for 100 United States CPI-U subcategories. We find that crucial changes in how agencies consider quality adjustment in products, together with the aforementioned macroeconomic variables help to understand CPI volatility over time, both in the short-run and in the long-run.

JEL codes: E30, E31.

Keywords: CPI inflation, volatility, volatility persistence, quality adjustment, panel data, GARCH.

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Literature has largely stablished that inflation volatility generates relevant costs for the real economy and, therefore, for welfare. *(Elder, 2004)* estimates that an average inflation volatility shock causes a reduction in the economic growth of U.S. of 22 basis points over three months. Their results are consistent for the whole 1966-2000 period of the analysis and different subperiods. *(Zivkov, et al., 2020)* find that inflation volatility has, indeed, larger negative effects on output growth than the level of inflation. This confirms *(Friedman, 1977)* hypothesis, who conjectured that an increased variability of actual or anticipated inflation may raise the natural rate of unemployment. Moreover, price instability promotes financial instability. Given these negative consequences, monetary authorities, as custodians of the financial system, have been concerned with inflation stability for decades (See, for instance, *(Goodfriend, 1987)*, *(Schwartz, 1995)* and *(Balatti, 2020)*).[1]

Another strand of literature, which explores Consumer Price Index (CPI) performance in detail, concludes that measured volatility for inflation is largely generated by changes in statistical agency methodologies. For instance, *(Detmeister & Hulseman, 2017)* find that much of the decline in the volatility of changes in monthly core inflation since the 1960s, for U.S., is a result of changes in seasonal adjustment techniques and rebasing. They claim that, if you account for this, there is little long-run trend in the series and no evidence of a Great Moderation in inflation volatility at a monthly frequency.

Finally, *(Tysklind, 2020)* focuses on the introduction of quality adjustments in CPI and runs an international comparison of CPI evolution from 2000 to 2018. The CPI subcategories that suffer from quality changes show significant differences among west European countries. Many of the

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[1] *See Figure 1 for the evolution of aggregate inflation and its trend and Figure 2 to notice the differences in the magnitude of the volatility for several CPI-U subcategories.*

goods in the quality-adjusted categories are highly tradable. However, the tradability condition does not fully explain the relative price movements, which are still present once you control for exchange rate variations. These differences are so large that they do have an effect on the aggregate CPI indexes.

From our point of view, these findings suggest that measurement issues are important to consider when policymakers have price stability as a target. Our paper sheds some light on the importance of the introduction of quality adjustments on inflation volatility. We develop a panel data analysis where individuals are 100 U.S. CPI-U subcategories over the maximum available time-span at monthly frequency to identify and separate the effects of the macroeconomic and methodologic factors explaining volatility of measured inflation.

One key change in CPI measurement by statistical agencies is the introduction of quality adjustments. These adjustments have been largely improved in the U.S. CPI and elsewhere over the years.[1] One big push in this direction came in response to the 1996 Boskin commission report *(Boskin, et al., 1996)*. This report lead to an expanded use of hedonic methods and more frequent updating of the goods in the consumer's basket used to calculate the CPI, *(Johnson, et al., 2006)*. Quality adjustments have also been increasingly important in price adjustments performed by the US Bureau of Economic Analysis (BEA) in the national accounts, *(Wasshausen & Moulton, 2006)*. They are quite significant in categories of goods that are of great importance to trade, such as vehicles, consumer electronics, or apparel and, focusing in 2017-2018 CPI-U item weights, categories affected by quality adjustment accounted for 47% of total CPI-U, being Shelter items a 33%.

In this paper, we take into account both conditional and unconditional forms of inflation variance. While the use of conditional variances may appear better suited to capture the effects of inflation uncertainty, there are good reasons to consider unconditional variances too. As (Rother, 2004) discusses, the fact that inflation expectations are not observable implies that results coming from conditional variance modelling only hold for the specific underlying model used to generate those aggregate inflation expectations. Any variation in the expectations model may result in different conclusions. Moreover, conditional and unconditional variability of inflation are highly positively correlated. Therefore, using unconditional variances could be expected to yield results broadly representative for inflation expectations, while eschewing the problems related to forecast modelling. However, the unconditional measure captures historical volatility by assigning equal weights to all observations regardless of the period to which they belong. When a series has time-varying volatility, the unconditional variance will miss these changes.

First, we use panel data linear regressions with fixed effects to explore the contemporaneous relationship between inflation volatility and macroeconomic and methodological explanatory variables. Second, we develop an Autoregressive Distributed Lag (ARDL) model to identify potential long-run links between variables. Our results show that both methodological and macroeconomic variables help to explain measured inflation volatility. The average or trend level of inflation is highly significant both in the short and the long-run, as they are quality adjustments. Third, we measure the conditional variance of inflation using a generalized autoregressive conditional heteroskedasticity (GARCH) model. We regress this measure on the same explanatory variables explored for the unconditional volatility. We regress this measure on the same explanatory variables explored for the unconditional volatility. We find that quality adjustments are highly significant. However, we are only able to apply this method on a reduced and balanced panel dataset. For this reason, we proceed to run the analysis with exponential weighted moving average (EWMA) volatility. The results for the latter analysis are robust to those found in the previous sections.

The rest of the paper is structured as follows: Section I details the dataset. Section II explores the contemporaneous relationship between inflation volatility and its explanatory variables. Section III analyze the long-term link. Section iv develops a GARCH measure of inflation volatility. Section V concludes.

i. Empirical Evidence

The dataset consists of a panel of 100 narrow categories of United States CPI-U for the entire available time series (1950m1-2020m9). The Bureau of Labor Statistics (BLS) offers CPI-U series, not seasonally adjusted, starting in 1950 at a monthly frequency. Although many subcategories were available later (See Table 5 for details).[2]

The choice between core and headline inflation as a suitable measure to analyse inflation volatility and as a target for central banks has been extensively discussed and the disagreement is still on the table (See, for instance *(Crone, et al., 2013)* and *(Mishkin, 2007)*). Indeed, *(Crone, et al., 2013)* find that food and energy prices are not the most volatile components of inflation, and that core might not be the best measure of total inflation. Therefore, although energy categories are included in the panel, we also explore the potential different outcomes for non-energy subcategories alone.

Different authors and agencies use different definitions of inflation on their analyses. For example, IMF and BLS use year-over-year CPI changes, while ECB studies focus on month-over-month CPI changes. Following *(Çekin & Valcarcel, 2020)*, we calculate two volatility measures for month-over-month and year-over-year inflation for each CPI category: the 5-year rolling window of the standard deviations of inflation; and the 5-year rolling window of the standard deviations of the cyclical component of inflation once Hodrick Prescott (HP) filter has been applied.[3] The regressions for

[2] For the first decades in our timeseries, CPI-U series were only available in their not-seasonally-adjusted version. Nevertheless, being worried about seasonality, we introduced monthly dummy variables to clean our results from its effects. All these dummies turned out to be not significant, even at the 10% confidence level. Remember that the dependent variables and the main independent variable are constructed over 36-months of data in an overlapping rolling window. This makes stationarity effects vanish.

[3] Calling *volatility* to the standard deviation of the cyclical component of a time series is somewhat misleading. We followed many authors in the use of this measure to explore the volatility of the deviations of a macroeconomic time series from its long-term path *(*see, for instance, (Afonso & Furceri, 2010) (Chauvet & Guillaumont, 2009); and (Hnatkovska & Loayza, 2005)). (Rizvi, et al., 2014) explains this measure is suitable to extract inflation volatility for countries where inflation series is suspected to be non-stationary.

month- over-month variables are in Tables 1 to *Table 5*. Tables *Table 1*, 2 and 3 use EER and σ_{EER} among the regressors, while Tables *Table 4* and *Table 5* consider the monetary policy variables. The text comments on the differences, if any, with year-over-year variable regressions.

In the analysis, we use four macroeconomic variables as potential explanatory variables: the nominal Narrow effective exchange rate, EER, series NNUSBIS from the Bank for International Settlements and retrieved from the Federal Reserve Bank of St. Louis; the monthly aggregate unemployment rate, U, also extracted from Federal Reserve Bank of St. Louis; and two monetary policy variables, the monthly growth of the monetary base and the monthly growth of the M3 index from OECD database. We also consider the volatility of all of them as regressors.

EER is the weighted geometric average of bilateral dollar exchange rates against the currencies of a selection of trading partners. The EERs are constructed using moving trade weights, computed on the basis of shares in U.S. external trade in manufactured goods and services. Therefore, it may account for the imported inflation volatility and for the transmission of asymmetric foreign business-cycles.[4] Movements in unemployment are linked to the point of the business cycle where the economy is in every period. Therefore, it allows us to account for over-the-cycle changes in inflation volatility with a variable (in real terms) that, unlike GDP or GNP, is not affected by how inflation is measured. Moreover, it also indirectly captures the effects of changes in labor market institutions on inflation volatility. Its relevance has been documented in *(Campolmi & Faia, 2011)*. They show that, when unemployment insurance schemes differ, reservation wages react differently in each country to common shocks. This implies that real marginal costs and inflation also react differently. They find evidence for EMU countries supporting the existence of a cross-country link over the

[4] The exchange rates react to asymmetric movements between internal and foreign monetary policies. Indeed, evidence indicates they react quickly, and they do it even more in periods in which interest rates are in the zero lower bound (See (Rosa, 2011)and (Holtemöller, et al., 2020)). Therefore, the use of EER instead of the import price indexes helps to capture the differential between foreign (imported) and national inflation; and the transmission of the asynchronized business-cycles among countries that trade (See (MacDonald & Swagel, 2000)).

cycle between labor market structures on the one side and real wages and inflation on the other.

As in *(Campolmi & Faia, 2011)*, we also explore the specific role of the Great Recession and the posterior period of the so-called quantitative easing in the monetary policy and zero-lower-bound on inflation volatility. To do so, we create a dummy variable turning 1 for all subcategories during the period 2007m12 to 2015m12. This 8-year period comprises the official recession period according to the Board of Governors of the Fed System and the period during which the Federal Reserve maintained a very loose monetary policy. Indeed, the Federal Reserve turned to a new monetary regime, out from the zero-lower-bound, in December 2015.

However, not all changes in the volatility of measured inflation come from changes in the economic environment. Some of them may be changes caused artificially, in the sense that statistical agencies modify their methodologies to improve measurement. To isolate these two sources of volatility dynamics, we introduce two new dummy variables.

First, *shelter83* is a binary dummy turning 1 for residence-related subcategories from period 1983m1 and being 0 before that. *(Detmeister & Hulseman, 2017)* explain how in 1983 the BLS implemented a significant change to the measurement of costs for homeowners, a cost which currently accounts for roughly one-quarter of CPI expenditures. Prior to 1983 shelter costs for homeowners were based on home purchase costs, mortgage costs, taxes, insurance, and repair costs. This series, showed a significant spike in volatility in the early 1980s, driven by increases in home mortgage rates. Since 1983 shelter costs for homeowners has been based on expected rental rates if a homeowner were to rent out their home, a concept called *owners' equivalent rent* or *imputed rent to owner-occupied housing*. The change in the measurement of housing costs occurred to separate the investment component of house prices from the part devoted to renting a place to provide shelter.

Second, quality adjustments to price indexes in the US and elsewhere have improved over the years. One big push in this direction came partly in response to the 1996 Boskin commission report *(Boskin, et al., 1996)*. This report leads to an expanded use of hedonic methods and more frequent updating of the goods in the consumer's basket used to calculate the CPI, *(Johnson, et al., 2006)*. Quality adjustments have also been increasingly important in price adjustments performed by the US Bureau of Economic Analysis (BEA) in the national accounts *(Wasshausen & Moulton, 2006)*; and they are quite significant in categories of goods such as vehicles, consumer electronics, or apparel.[2] Hence, we create dummy *Q* which turns 1 from the month in which BLS starts applying quality adjustments to a CPI-U subcategory onwards. Q is zero for the entire series when a subcategory is not subject to quality adjustments or in periods previous to their introduction. *Table 7* details which categories are subject to such quality considerations and since when. The complete list of items subject to quality change adjustments in U.S. CPI-U is available in BLS web-page. There is no detailed list pairing this item list and the date of quality adjustment introduction. We collected this information from the following sources: *(Wells & Restieaux, 2014)*, *(Stewart & Reed, 1999)*, and *(BLS, 2020)*.

ii. Level of inflation on volatility

In this section, we study the connection between the measured inflation volatility and the level of inflation and other macroeconomic and methodologic variables. We use linear ordinary least square regressions for panel data following this equation:

(1) $$\sigma^{\pi} = a + \beta\pi_{i,t} + \gamma x_{i,t} + \delta z_t + \varphi c_i + \mu_{i,t},$$

where the error term, μ, is robust to heteroskedasticity and serial correlation, and we include fixed effects.[5] Subindex t indicates the month. Β is the coefficient associated to one of the three measures of (average) inflation per subcategory used in the models; x_i is the vector of dummy variables; z,

[5] The use of robust errors to correct for our problems of heteroskedasticity and serial correlation is not always the optimal solution. We follow (King & Roberts, 2015) and run our regressions both with normal standard errors and with robust errors. Then, we observe whether they differ substantially. For all our regressions, errors vary only slightly, and coefficient significances do not change. The only exception is found in the standard errors for the coefficient of π, which turns to be only significant at the 10% level with robust standard errors. Therefore, we conclude that the use of robust errors does not hide, in our case, a problem of misspecification.

is a vector of variables with common values for every CPI subcategory. The latter help us control for the common effects of the economic cycle on subcategories. It may include the standard deviation of national unemployment rate (σ_U),[6] the standard deviation of the effective exchange rate (σ_{EER}) and the EER variation from last period; the monthly change of the log of the monetary base (g_{mb}) or the monthly growth of the M3 broad money index (g_{mbr}); and their volatilities ($\sigma_{g_{mb}}$ and $\sigma_{g_{mbr}}$). Among the dummy variables we consider *crisis*, a dummy that takes value 1 for all subcategories from period 2007m12 to 2015m12 to account for the consequences of the financial crisis, *shelter1983* that takes value 1 from 1983m1 in subcategories related to shelter, and Q, which turns 1 in the period in which quality adjustment was introduced for each category.

As discussed in *(Arespa & Gruber, 2021)*, one concern the reader may have is the possible coincidence in time of globalization upsurge and quality adjustment methods in CPI. If this was the case, we could erroneously conclude on the relevance of quality changes consideration, while part of the hidden effects could come, instead, from trade openness. Literature locates most relevant regulatory changes which favor openness between 1970 and 1995 (see, for instance, *(Krugman, 1995)* and *(Sachs & Warner, 1995)*). *(Ben-David & Papell, 1997)* develop a detailed cross-country time series analysis testing for structural breaks in imports and exports over GDP ratios. They find 1972 and 1973 as breaking points for US imports and exports over GDP ratios. All of the 47 analyzed countries suffered the break in 1986 the latest and there is quite a lot of variety in the break date. In a more recent paper, *(Husein & Pier, 2019)* look for structural breaks for US exports and imports endogenously and find them around 2007. Finally, we run a simple analysis for annual import and export data from 1960 to 2019 and systematically reject the hypothesis of a structural break in their trends around years close to 1998, where major quality adjustment changes were

[6] The level of unemployment and its monthly growth turned to be not significant, and its inclusion or exclusion caused no changes in the rest of coefficients.

introduced in CPI.[7]

Tables *Table 1* to *Table 3* contain the regression results for models with EER or its volatility as explanatory variables. Columns 2 to 5 in every table have the standard deviation of 60-month rolling-window of month-over-month inflation as dependent variable, while Columns 6 to 9 use the standard deviation of the same rolling-window for the cyclical part of the HP-filtered inflation as dependent variable. Models 1 and 2, labelled "*headline*" use all 100 considered subcategories; instead, Models 3 and 4, labelled "*core*" do not include energy subcategories.

TABLE 1 HERE

TABLE Table 2 HERE

TABLE Table 3 HERE

The first outcome that Table 1, Table 2 and Table 3 reveal is the fact that, today's level of inflation is not relevant to determine inflation volatility, measured over an overlapping rolling window of 60 months. Instead, the two measures of average inflation are highly significant. Our results are consistent with Friedman's hypothesis (Friedman, 1977) and show positive signs for coefficients β: higher (average or trend) inflation imply higher inflation uncertainty.

Second, although coefficients are small, compared to those of average inflation, the two dummy variables related to methodological changes (shelter83 and Q) are highly significant in the three tables. Regarding the macroeconomic variables with common values for all subcategories, we see how crisis and unemployment volatility, σ_u, are significant at 1% in all models. Crisis has a negative coefficient in all regressions. Although it is the smallest coefficient we obtain, it indicates that during the period comprised between the beginning of 2008 financial crisis and the end of the quantitative-easing policy inflation volatility behaved significantly different compared to the rest of the period in the analysis. Indeed, it was a period with a slightly lower volatility in prices.

The volatility of unemployment is generally linked to the business cycle. The intuition goes as follows: during recessions, the cost of risk increases sharply, the benefit from creating new

[7] See BIS manual for details on the construction of EER indices.

matches drops, leading to a large decline in job vacancies and an increase in unemployment (Kehoe, et al., 2020). Investments in hiring workers are highly cyclical and, consequently, the volatility of job-finding rates and of unemployment are also cyclical. The coefficient in our regressions is positive, indicating, precisely, that the more volatile unemployment is, the more volatile inflation becomes. Therefore, inflation tends to be more volatile during downturns.[8]

In Tables Table 2 and Table 3, the variation of the real effective exchange rate is only significant when we include energy-related subcategories within the panels and the dummy variable crisis is not considered. The first of these results is driven by oil-related products. Clearly, the variation of the exchange rate is crucially transmitted to the price of goods that are homogeneous worldwide and that are only produced by a few, like fuels. The second is due to the fact that REER variations were very large during 2008 financial crisis, compared to previous and posterior dates, coinciding with *crisis* dummy taking value 1 in our timeseries.

As *(Detmeister & Hulseman, 2017)* identified, the changes introduced in the measuring of shelter in CPI subcategories in U.S. reduced the volatility of prices. When we consider energy-related subcategories, an increase of the effective exchange rate index (i.e., an appreciation of U.S. dollar with respect to the weighted-basket of trading-partner currencies)[9] reduces the volatility of inflation. Finally, we see how larger volatility in the real economy, measured via unemployment volatility, causes an increase in inflation volatility.[10]

Tables *Table 5* and *Table 6* contain the regression results for models with monetary aggregates as explanatory variables.[11,12] First, the monetary base growth is never significant in our regressions, whilst the broad money growth is. Second, the volatility of both monetary aggregates is significant. σ_{mbr}, the

[8] (Andolfatto, 1997) shows how unemployment rate increases sharply during recessions, while during expansions, it declines only gradually.

[10] In the regressions with inflation, EER and unemployment variations computed as year-over-year change, our main conclusions are still valid. However, the coefficients for EER and its volatility are highly significant and positive, except for the combination of inflation in levels as the main regressor and its volatility as dependent variable. Moreover, for the latter combination, the coefficient of inflation in levels turns significant and, this is true regardless of the use of robust or normal residuals. Finally, when variables are computed for year-over-year changes, the coefficient for *crisis* changes sign (becoming now positive) and it is significant at 1%.

[11] These models are not included in tables Table 1 to Table 3 for space reasons.

[12] The introduction of the monetary aggregates in the regression, together with EER or the volatility of EER makes the former or the latter become no-significant, and the coefficient of EER variables vary considerably. This is not surprising, since EER is an exchange rate measure, which is crucially affected by monetary policy. The models with both blocks of variables are not displayed to save space.

volatility of the monthly growth of the M3 index, has a negative coefficient regardless of the dependent variable and of the indicator of the level of inflation used in the regression. This implies that prices respond less to monetary policy changes when this policy varies a lot. When the monetary supply changes frequently, it might not be optimal for many agents to adjust prices; moreover, short-term nominal rigidities may prevent these adjustments. When we turn our attention to σ_{mb}, the volatility of the monthly growth of the monetary base, we see its coefficient is also negative when the indicator of the level of inflation is inflation per se, π_t. However, when we use a measure of the average inflation ($\bar{\pi}_t^{HP}$ or $\bar{\pi}_t$) as a regressor, whose coefficients are significant, the coefficient of σ_{mb} becomes positive. The two aggregates give different information to markets. The monetary base has followed a moderate and linearly positive trend over the last sixty years. M3 has increased exponentially. The former is more tightly controlled by the Federal Reserve, while M3 is affected by the financial markets. Therefore, the setters of goods prices follow the evolution of the monetary base closely, as an indicator of future inflation, and adjust prices accordingly. So, prices are more volatile when M1 is. Instead, price setters follow a wait-and-see strategy when M3 (but not M1) is more volatile, and avoid adjusting prices.[13] Finally, the dummy variable *crisis* loses significance with the introduction of the monetary policy variables. The rest of coefficients and their significance level do not vary in any appreciable way compared to regressions in Tables *Table 1* to *Table 3*.

TABLE Table 5 HERE
TABLE Table 6 HERE

Tables *Table 5 and Table 6* only report the regressions for the headline inflation (as we define it). The conclusions for our definition of core inflation are similar. The relevant difference is that the broad aggregate is no significant either and only the volatility of the monetary aggregates helps to explain inflation volatility.

iii. ARDL or Dynamic Panel Data Models

A large strand of literature finds inflation rate quite persistent (see, for instance, *(Weber, 2018)*, *(Fuhrer, 2010)* and *(Cogley & Sbordone, 2008)*). Nevertheless, only a few bunch of studies, like that of *(Çekin & Valcarcel, 2020)*, explore the persistence of inflation volatility. In this section,

[13] The correlation between the changes in the monetary base and in M3 index is 0.34 when one considers the entire period. However, it reduces to 0.05 and becomes not significantly different from 0 for the period before 2007m12. For 2016-2020, the correlation increases to 0.79.

we allow inflation volatility to have a long-run relationship with inflation rate, apart from the contemporaneous link already analysed in Section ii.

First, we run Im-Pesaran-Shin and Fisher-type (Dicky-Fuller) unit root tests for the unbalanced panel, over the different long-run inflation component and inflation volatility variables at play. The null hypothesis for both tests is H_0: All panels contain unitroot. The null hypothesis is systematically rejected for our dependent variables *(σ^{π} and $\sigma^{\pi^{HP}}$)*, and it is systematically accepted for the long-run inflation components *($\bar{\pi}^{HP}$, $\bar{\pi}$ and π)*. Levin–Lin–Chu tests for one-by-one CPI subcategories on the dependent variables give mixed results. Therefore, the panel contains both stationary and unit root individuals, regarding the measure of the volatility of inflation we use. Finally, running Hadri (lagrangian multiplier) test on the volatility variables for a sub-period in which the panel is balanced one concludes that not all individuals are stationary. In this test, the null is H_0: all panels are stationary. Consecutive tests on first differences of dependent and long-run inflation variables discard I(2).

Autoregressive Distributed Lag (ARDL) models allow us to deal with the present scenario of mixture of unit root and stationary series and analyse, simultaneously, the contemporaneous and long-run relationship between variables. We combine three methods to select the suitable number of lags in equation (2). First, the Schwarz (Bayes) and AIC criterion, after adjusting the penalty value for the test to $ln(\sqrt{nT})/(\sqrt{nT})$ following *(Han, et al., 2017)* to avoid the inconsistency and overestimation of the true lag length in dynamic panels. These tests suggest the introduction of one lag for the dependent variable and two lags for the measures of the inflation level. Second, we consider the Global Search Regression engine by *(Gluzmann & Panigo, 2015)*. It recommends using two lags for the dependent and no lag for the trend inflation. And finally, we directly observe the sign changes and coefficient variations after the introduction of lag 1 and lag 2 for the dependent and independent variables. We conclude that the most reasonable model is that with one lag for the dependent variable and none for the trade inflation measure.[4] Therefore, we formulate the following model:

$$(2) \qquad y_{it} = \beta_i + \beta_i y_{i,t-1} + \beta_i x_t + \theta z_{it} + e_{it},$$

were x is the vector of explanatory variables common to all panel units and z is the vector of explanatory variables which values differ per panel unit. The latter includes quality adjustments, Q; the level of inflation, $\bar{\pi}^{HP}\bar{\pi}$ or π; and the *crisis* and *shelter1983* dummies. In the regression, we use robust residuals and cluster errors at the unit (individual) level to control for cross-sectional dependence. Not doing so would invalidate the ARDL model. Any of Westerlund and Pedroni's cointegration tests, but v–test, reject the null hypothesis of no-cointegration at the 1% level of significance. Therefore, there exists a long-run relationship between the dependent and the independent variables. We can now proceed to estimate the model in equation (2) to analyse the long-run links.

Table 6 shows the results for the model in equation *(2)*. Estimates suggest that inflation volatility is a highly persistent process. Once you have accounted for this persistency, the coefficients for quality adjustments, *Q*, and for s*helter83*, are still significant at 1%. Therefore, methodological changes do have a long-run effect on inflation volatility. The (average) level of inflation is also significant for the long-run. However, when the regressor is $\bar{\pi}^{HP}$, the significance level is smaller than in the short-run relationship analysis. Other macroeconomic variables, like unemployment volatility and the real effective exchange rate are no longer significant, suggesting there is not a long-run relationship between inflation volatility and these two variables.

iv. A GARCH measure for inflation volatility

In the previous sections we explored the unconditional volatility of inflation. There, we use standard deviations, which capture the historical volatility, assigning equal weights to all observations regardless of the period to which they belong. In this section, we move to the conditional variability of inflation by using a GARCH measure for inflation volatility.

To study the time-varying variability of inflation, one could use an ARCH model by choosing the appropriate number of lags. However, the ARCH model requires a long lag process of the squared residuals to explain volatility. To circumvent this problem, (Bollerslev, 1986) and (Taylor, 1986) independently developed the Generalised ARCH (GARCH) model in which the conditional variance is considered as a function of the lagged values of shocks and conditional variance itself. As (Banerjee, 2017) discusses, the major advantages of the GARCH (1,1) are that the model is parsimonious; it avoids the over-fitting problem; and it is less likely for breaching the non-negativity constraints on the estimable parameters. Moreover, it can capture the effect of infinite number of past squared residuals on current volatility with only three parameters. One disadvantage is that it enforces a symmetric response of volatility to positive and negative shocks. Following this limitation, other variants of the GARCH model were developed to analyse the nature and impact of shocks. However, (Hansen & Lunde, 2005) shows how GARCH (1,1) process is, at least, as good as any other competing model of volatility. Based on their results, we stick to GARCH (1,1) to explore the quantitative analysis of inflation volatility.

Construction of the mean equation

Following (Rizvi, et al., 2014) and (Hassan, et al., 2018), we calculate inflation growth rates on a year-on-year basis by taking twelve-lagged difference of natural logarithms of the CPI series.

As in (Rizvi, et al., 2014) we model inflation dynamically through an autoregressive process. There are certain economic and financial variables that are widely believed to be important determinants of inflation. However, several studies concluded that none of the single indicators generally included for its importance as inflation determinants were able to improve the forecasts of the autoregressive model clearly and consistently (See (Cecchetti, et al., 2000) and (Binner, et al., 2009)). For this reason and given that we are interested in extracting a measure for inflation volatility and not in explaining inflation per se, we stick to the autoregressive process for the panel data mean equation in ():

(3) $$\pi_{it}^{a} = \lambda_i + \sum_{s=1}^{k} \delta_s \pi_{it-s}^{a} + u_{it},$$

where λ captures possible time-invariant effects associated with inflation rates and u_{it} is a disturbance term.

The Global Search Regression engine by (Gluzmann & Panigo, 2015) indicates that an AR(2) is the most suitable lag-length for inflation. Moreover, postestimation Cumby-Huizinga test indicates that there is no evidence of autocorrelation in our residuals at any lag-length between 1 and 4. Thus, we can specify the following conditional moments for u_{it}:

(4) $$E[u_{it}u_{js}|u_{it-1}, u_{js-1}] = 0 \qquad for\ i \neq j\ and\ t \neq s,$$

(5) $$E[u_{it}u_{js}|u_{it-1}, u_{js-1}] = 0 \qquad for\ i = j\ and\ t \neq s,$$

(6) $$E[u_{it}u_{js}|u_{it-1}, u_{js-1}] = \sigma^2_{ij,t} \qquad for\ i = j\ and\ t \neq s,$$

(7) $$E[u_{it}u_{js}|u_{it-1}, u_{js-1}] = \sigma^2_{ij,t} \qquad for\ i \neq j\ and\ t = s,$$

(8) $$E[u_{it}u_{js}|u_{it-1}, u_{js-1}] = \sigma^2_{i,t} \qquad for\ i = j\ and\ t \neq s,$$

Conditions in (4) and (5) assume no non-contemporaneous cross-section correlation and no autocorrelation, respectively. Assumptions in (7) and (8) are general conditions of the conditional variance-covariance process.

Stationarity of inflation

We run Im-Pesaran-Shin and Fisher-type (Dicky-Fuller) unitroot tests for the unbalanced panel, and Hadri (lagrangian multiplier) test for a sub-period in which the panel is balanced, for π^a_{it}. As in Section iii, we conclude that not all individuals are stationary. Therefore, the panel contains both stationary and unit root individuals. (Rizvi, et al., 2014) discuss how the model in equation () may arise some concerns if the inflation series is found to be non-stationary. To address this issue, they propose to model the cyclical component of inflation, obtained from the Hodrick–Prescott (HP) filter, instead of inflation to capture conditional variance or inflation volatility through GARCH specifications. Consequently, we model π^{HPa} (the cyclic component of year-over-year inflation), as well as π^a. The structure of the model is the same specified in Equation ():

(9) $$\pi^{HPa}_{it} = \lambda_i + \sum_{s=1}^{k} \delta_s \pi^{HPa}_{it-s} + u_{it},$$

The conditional variance-covariance equations

The conditional variance-covariance process of u_{it} is assumed to follow a GARCH(1,1) process:

(10) $$\sigma^2_{it} = \alpha_i + \delta\sigma^2_{it-1} + \gamma u^2_{it-1} + \beta x_t + \theta z_{it}$$

(11) $$\sigma_{ijt} = \eta \quad + \delta_c \sigma_{ij,t-1} + \gamma_c u_{i,t-1}u_{j,t-1}\ for\ i \neq j$$

where σ_{it}^2 is the conditional variance, σ_{ijt} is the conditional covariance, x is a vector of the all-panel common-value control variables like unemployment volatility or the monetary variables, and z is a vector of the panel-specific explanatory variables (quality adjustments and the level or average inflation). Notice that equations (10) and (11) imply that the conditional variance and covariance processes follow the same dynamics, not that they are identical among units or pairs of units respectively. Assuming that the resulting variance-covariance matrix is positive definite at each point in time and that it converges to some fixed positive definite matrix, this unconditionally model is a pooled panel data model with cross-sectionally correlated disturbances (See (Cermeño & Grier, 2006)).

Since the model is no longer of the usual linear form, OLS cannot be used for GARCH model estimation. Notice that OLS minimizes the residual sum of squares (RSS) and, this minimization depends only on the parameters in the conditional mean equation, and not the conditional variance. Hence, RSS minimization is no longer an appropriate objective. Hence, we move to the maximum likelihood technique. The log-likelihood function (LLF) for the complete panel is given by:

$$L = -\frac{NT}{2} ln(2\Pi) - \frac{1}{2}\sum_{t=1}^{T} ln(\sigma_t^2) - \frac{1}{2}\sum_{t=1}^{T}(\pi_{it}^a - \lambda_i - \sum_{s=1}^{k} \delta_s \pi_{it-s}^a) / \sigma_t^2 \quad (12)$$

Data

To estimate a panel GARCH we must adjust our dataset in its two dimensions. First, we must reduce the time span and the number of subcategories to work with a balanced panel. GARCH models are not good at handling any sort of missing data points because they depend upon a recursion for estimating the variances. Therefore, we decided to restrict our panel to subcategories with available data between 1982m12 and 2020m9. Several CPI subcategories start in this date, and it is a date point far enough from the introduction of the most relevant quality adjustment (see Table 7). This left us with 58 panels. Moreover, we renounced to consider *shelter1983* among our regressors because this dummy would take value 1 for the whole considered period.

Second, we must further reduce the number of individuals in our panels for computational reasons. Panel GARCH model implies an unrestricted n x n symmetric matrix of free parameters to be estimated in recursion. For a panel of 58 individuals, it represents around 1800 free parameters and standard econometric software cannot handle it.[14] Consequently, we limited the dataset to 16 panels. We include 9 subcategories subject to quality adjustments and 7 without. We avoided the inclusion of energy-related and services categories (The * next to the description name in Table 7 indicates the inclusion of a subcategory in the panel GARCH regressions.)

Results

Table XX shows the results for the four panel GARCH model estimations. Model A and C are simply a panel extended version of the GARCH model with the conditional covariance equation. Models A and C use the first difference of the log of inflation,[15] and the hp-filtered log-inflation respectively, as dependent variable in the conditional mean equation. Models B and D include explanatory variables in the conditional variance equation.[16] Among them, there is the dependent variable used in the corresponding mean equation. Model B uses the variation of log-unemployment, whereas model D uses the hp-filtered log-unemployment.

All four models include category-specific effects, that are not reported to save space.

v. Conclusions

There is a large consensus among monetary authorities and academia regarding the relevance of achieving certain stability of prices. Indeed, many of the major central banks in the world have, nowadays, the control of inflation as a target, with an eye on inflation volatility.

The empirical findings in our paper are in line with the extensive literature that gives support to the positive link it exists between average or trend inflation and inflation volatility. Indeed, we find that this relationship is significant both in the short and in the long-run. Therefore, we also back up modern central banking strategy in this regards. However, our results arise an issue that has been barely considered in the past: measured inflation volatility

[14] We use RATS software for panel GARCH estimations. The rest of outputs (estimations and tests) are obtained with Stata.

[15] We use the variable in differences to ensure its stationarity.

[16] See (Deniz, et al., 2021) for the first paper that includes independent variables in the conditional equations.

contains and hides the effects of methodological decisions carried out by statistical agencies. These effects are statistically relevant in our panel data analysis. Moreover, the level of quality of products in the basket of consumption is constantly changing in the short run (See *(Johnson, et al., 2006)* and *(Wasshausen & Moulton, 2006)* for an empirical discussion and *(Arespa & Gruber, 2021)* for a theoretical analysis). Consequently, if the scope of a central bank is to stabilize the measure of a cost-of-living index, it should reflect on how much quality adjustments over the business cycle are conditioning its target and on whether the statistical agency has introduced recent and relevant modifications in its measuring methods.

Declarations statements

Data available on request from the authors.
No potential competing interest was reported by the authors.

Acknowledgements

Marta Arespa gratefully acknowledges financial support from the Spanish Ministry of Science, Innovation and Universities through grants PGC2018-094364-B-100 and RTI2018-093543-B-I00, MCIU/AEI/ FEDER, UE.

The authors are thankful to Pinar Deniz, Thanasis Stengos and Thomas A. Doan for the helpful comments and discussions.

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APPENDIX

Details on CPI subcategories

The complete list of items subject to quality change adjustments in US CPI- U is available in https://www.bls.gov/cpi/quality-adjustment/. There is no detailed list pairing this item list and the date of quality adjustment introduction. We collected this information from the following sources: *(Wells & Restieaux, 2014)*, *(Stewart & Reed, 1999)* and *(BLS, 2020)*. Moreover, the list of items subject to quality adjustments are coded by the BLS Consumer Price Index Entry Level Items (ELIs), whereas CPI-U has its own coding, which is not as disaggregated. We have paired them based on the definitions of CPI-U categories.

We follow *(Johnson, 2017)* to classify every subcategory as tradable or as non-tradable. He uses total commodity output from Input-Output tables provided by the Bureau of Economic Analysis and defines a threshold over which a commodity becomes tradable. To choose the threshold, he measures tradable-non-tradable classification stability as the number of industries that changed their condition owing to a 1-percentage-point increase or decrease from the threshold. For example, if the threshold in question was 15 percent, the stability measure was the number of industries that went from tradable to nontradable, and vice versa, as a result of moving the threshold to 14 per- cent or 16 percent. After a robustness check, he concludes that the suitable threshold for US is 11% of GDP. Table A-1 in his appendix provides the full list of items classified. Once a CPI category is identified as tradable, our trade dummy variable turns to 1 for the whole-time span.

Monthly unemployment rate is extracted from US Bureau of Labor Statis- tics, Unemployment Rate [UNRATENSA], retrieved from FRED, Federal Re- serve Bank of St. Louis (https://fred.stlouisfed.org/series/UNRATENSA); annual Import and Export data is from United States Census Bureau;[5] US GDP is from Leading Indicators OECD: Reference series: Gross Domestic Product (GDP): Normalized for the United States [USALORSG- PNOSTSAM], retrieved from FRED, Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/series/USALORSGPNOSTSAM).

Table 5 lists the CPI categories with their codes, their classification as tradable or non tradable, the date of new quality adjustments if any, and the length of the time series.

TABLE Table 7
HERE

Table 1: Panel data linear regressions for CPI volatility over inflation in levels.

	σ_t^{Π}				$\sigma_t^{\pi^{HP}}$			
	headline		*core*		*headline*		*core*	
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
π_t	.0045	.0042	0.0059	.0018	.0039	.0036	.0051	.0012
	(.0046)	(.0046)	(.0044)	(.0038)	(.0046)	(.0046)	(.0043)	(.0037)
EERm	.0016		.0042***		.0005		.0033**	
	(.0019)		(.0016)		(.0019)		(.0016)	
σ_{EER}	.0030	.0388***			.0045	.0379***		
	(.0129)	(.0138)			(.0127)	(.0136)		
Q	.0024***	.0026***	.0026***	.0034***	.0024***	.0026***	.0026***	.0034***
	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)
σ_U	.0216***	.0227***	.0269***	.0381***	.0192***	.0203***	.0247***	.0364***
	(.0013)	(.0013)	(.0013)	(.0011)	(.0012)	(.0013)	(.0012)	(.0011)
shelter83	−.0014***	−.0016***	−.0014***	.0005***	−.0015***	−.0017***	−.0015***	−.0006***
	(.0002)	(.0002)	(.0001)	(.0002)	(.0002)	(.0002)	(.0001)	(.0002)
crisis		−.0007***		−.0015***		−.0006***		−.0015***
		(.0001)		(.0001)		(.0001)		(.0001)
R-squared	.7239	.7243	.7539	.7786	.7237	.7240	.7568	.7810
Adj R-sq	.7232	.7236	.7533	.7781	.7230	.7233	.7562	.7805
Prob>F	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000
Obs	43578	43578	42274	42274	43578	43578	42274	42274
Categories	100	100	97	97	100	100	97	97

*Notes: The standard deviations are in parentheses. *, **, *** - statistically significant at the 10, 5, and 1 per cent.*

The dependent variables are the standard deviation of the 5-year month-over-month rolling window of each CPI-U subcategory of: inflation, σ_t^{π}; and of the cyclical part of HP-filtered inflation, $\sigma_t^{\pi HP}$. Models use narrow CPI subcategories only, discarding CPI all items and main subcategory aggregates. 'Core' models do not include energy-related variables. 'Headline' models use all narrow subcategories included in the study. σ_U is the standard deviation of the 5-year rolling window hp-filtered log-unemployment.

Table 2: Panel data linear regressions for CPI volatility over average HP-filtered inflation.

	σ_t^{π}				$\sigma_t^{\pi^{\mathrm{HP}}}$			
	headline		*core*		*headline*		*core*	
	(1)	*(2)*	*(3)*	*(4)*	*(1)*	*(2)*	*(3)*	*(4)*
$\overline{\pi}_t^{HP}$	.5976***	.5928***	.6611***	.5511***	.5394***	.5344***	.6002***	.4911***
	(.0226)	(.0228)	(.0208)	(.0205)	(.0226)	(.0227)	(.0205)	(.0202)
EERm	−.0032**		-.0004		−.0038***		−.0009	
	(.0019)		(.0016)		(.0019)		(.0016)	
σ_{EER}	.0057	.0156			.0070	.0170		
	(.0125)	(.0134)			(.0123)	(.0132)		
Q	.0048***	.0048***	.0051***	.0053***	.0045***	.0046***	.0049***	.0051***
	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)
σ_U	.0120***	.0125***	.0174***	.0351***	.0106***	.0112***	.0161***	.0337***
	(.0012)	(.0012)	(.0011)	(.0011)	(.0012)	(.0012)	(.0011)	(.0011)
shelter83	−.0031***	−.0031***	−.0034***	−.0022***	−.0030***	−.0030***	−.0033***	−.0022***
	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)
crisis		−.0002***		−.0012***		−.0002***		−.0012***
		(.0001)		(.0001)		(.0001)		(.0001)
R-squared	.7360	.7360	.7683	.7873	.7336	.7337	.7688	.7879
Adj R-sq	.7354	.7354	.7678	.7868	.7330	.7330	.7682	.7974
Prob>F	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000
Obs	43578	43578	42274	42274	43578	43578	42274	44463
Categories	100	100	97	97	100	100	97	97

*Notes: The standard deviations are in parentheses. *, **, *** - statistically significant at the 10, 5, and 1 per cent. The dependent variables are the standard deviation of the 5-year month-over-month rolling window of each CPI-U subcategory of: inflation, σ_t^{π}; and of the cyclical part of HP-filtered inflation, $\sigma_t^{\pi^{HP}}$. Models use narrow CPI subcategories only, discarding CPI all items and main subcategory aggregates. 'Core' models do not include energy-related variables. 'Headline' models use all narrow subcategories included in the study. σ_U is the standard deviation of the 5-year rolling window hp-filtered log-unemployment.*

Table 3: *Panel data linear regressions for CPI volatility over average inflation.*

	σ_t^{π}				$\sigma_t^{\pi^{HP}}$			
	headline		*core*		*headline*		*core*	
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$\bar{\pi}_t$	.5687***	.5631***	.6430***	.5429***	.5116***	.5058***	.5821***	.4834***
	(.0214)	(.0214)	(.0200)	(.0197)	(.0214)	(.0214)	(.0198)	(.0195)
EERm	−.0043***		-.0016		−.0047***		-.0019	
	(.0019)		(.0016)		(.0019)		(.0016)	
σ_{EER}	.0050	.0185			.0064	.0196		
	(.0125)	(.0134)			(.0124)	(.0132)		
Q	.0046***	.0047***	.0050***	.0053***	.0044***	.0045***	.0048***	.0051***
	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)
σ_U	.0126***	.0133***	.0178***	.0353***	.0111***	.0118***	.0165***	.0339***
	(.0012)	(.0012)	(.0011)	(.0011)	(.0012)	(.0012)	(.0011)	(.0011)
shelter83	−.0030***	−.0030***	−.0033***	−.0022***	−.0029***	−.0030***	−.0032***	−.0021***
	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)
crisis		−.0002***		−.0013***		−.0002***		−.0013***
		(.0001)		(.0001)		(.0001)		(0001)
R-squared	.7364	.7364	.7692	.7880	.7339	.7339	.7694	.7885
Adj R-sq	.7358	.7358	.7687	.7876	.7333	.7333	.7689	.7881
Prob>F	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000
Obs	43578	43578	42274	44463	43578	43578	42274	44463
Categories	100	100	97	97	100	100	97	97

*Notes: The standard deviations are in parentheses. *, **, *** - statistically significant at the 10, 5, and 1 per cent. The dependent variables are the standard deviation of the 5-year month-over-month rolling window of each CPI-U subcategory of: inflation, σ_t^{π}; and of the cyclical part of HP-filtered inflation, $\sigma_t^{\pi^{HP}}$. Models use narrow CPI subcategories only, discarding CPI all items and main subcategory aggregates. 'Core' models do not include energy-related variables. 'Headline' models use all narrow subcategories included in the study. σ_U is the standard deviation of the 5-year rolling window hp-filtered log-unemployment.*

Table 4: ARDL models

	σ_t^{π}			$\sigma_t^{\pi^{HP}}$		
	π_t	$\bar{\pi}_t^{HP}$	$\bar{\pi}_t$	π_t	$\bar{\pi}_t^{HP}$	$\bar{\pi}_t$
y_{t-1}	.99666***	.99620***	.99528***	.99690***	.99653***	.99572***
	(.0006)	(.0008)	(.0011)	(.0006)	(.0007)	(.0010)
x_t	.00604***	.00575**	.0163***	.00585***	.0048*	.01496***
	(.0020)	(.0031)	(.0055)	(.0019)	(.0029)	(0053)
Q	.00005***	.00006***	.0001***	.00005***	.00005***	.00009***
	(.0000)	(.0000)	(0000)	(0000)	(.0000)	(.0000)
σ_{EER}	-.00119	-.00204	-.00226	-.0008	-.00160	-.0018
	(.0013)	(.0014)	(.0015)	(.0013)	(.0013)	(.0015)
shelter83	−.00003***	−.00003***	−.00006***	−.00003***	−.00003***	−.00005***
	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)
Crisis	-.00001	-.00001	-.00001	−.00001**	−.00001**	-.00001
	(0000)	(.0000)	(.0000)	(.0000)	(0000)	(.0000)
R-squared	.9980	.9980	.9980	.9982	.9981	.9981
Adj R-sq	.9980	.9980	.9980	.9981	.9981	.9981
Obs	43497	43497	43497	43497	43497	43497
Categories	100	100	100	100	100	100

Notes: The standard deviations are in parentheses. *, **, *** - statistically significant at the 10, 5, and 1 per cent. The dependent variables are the standard deviation of the 5-year month-over-month rolling window of each CPI-U subcategory of: inflation, σ^{π}; and of the cyclical part of HP-filtered inflation, $\sigma^{\pi^{HP}}$. Models use narrow CPI subcategories only, discarding CPI all items and main subcategory aggregates. y_{t-1} is the first lag of the dependent variable (σ^{π} or $\sigma^{\pi^{HP}}$). x_t refers to the average inflation (π_t, $\bar{\pi}^{HP}$ or $\bar{\pi}_t$)

Table 5: Linear regressions with monetary policy variables for σ_t^{π} as dependent variable.

	π_t		π_t^{HP}		π_t	
x_t	.0038	.0034	.6029***	.5761***	.5742***	.5493***
	(.0043)	(.0043)	(.0226)	(.0227)	(.0212)	(.0213)
Q	.0029***	.0030***	.0049***	.0050***	.0048***	.0049***
	(.0001)	(.0001)	(.0002)	(.0002)	(.0002)	(0002)
σ_U	.0244***	.0382***	.0119***	.0236***	.0125***	.0245***
	(.0014)	(.0018)	(.0014)	(.0017)	(.0014)	(.0017)
shelter83	−.0014***	−.0010***	−.0034***	−.0030***	−.0033***	−.0029***
	(.0001)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)
Crisis	.0000	−.0002***	−.0004***	−.0000	−.0004***	-.0000
	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)
g_{mb}	.0004		-.0001		−.0002	
	(.0012)		(.0012)		*(.0012)*	
σ_{mb}	−.0232***		.0083***		.0093***	
	(.0038)		(.0036)		(.0035)	
g_{mbr}		−.0207***		−.0187***		−.0197***
		(.0067)		(.0063)		(.0067)
σ_{mbr}		−.6239***		−.3814***		−.3892***
		(.0465)		*(.0453)*		(.0444)
R-squared	.7298	.7312	.7412	.7418	.7416	.7422
Adj R-sq	.7291	.7306	.7405	.7412	.7409	.7416
Obs	44718	44718	44718	44718	44718	44718
Categories	100	100	100	100	100	100

Notes: The standard deviations are in parentheses. *, **, *** - statistically significant at the 10, 5, and 1 per cent. The dependent variable is the standard deviation of the 5-year month-over-month rolling window of each CPI-U subcategory of: inflation, σ^{π}_t Models use narrow CPI subcategories only, discarding CPI all items and main subcategory aggregates. x_t refers to the average inflation (π_t, π^{HP} or π_t). g_{mb} and g_{mbr} are the monthly change of the monetary base and of the M3 index; and σ_{mb} and σ_{mbr} are the standard deviation of the 5-year month-over-month rolling window of each of them.

Table 6: Linear regressions with monetary policy variables for $\sigma_t^{\pi^{HP}}$ as dependent variable.

	π_t		π_t^{HP}		π_t	
x_t	.0033	.0029	.5438***	.5176***	.5163***	.4920***
	(.0043)	(.0043)	(.0226)	(.0227)	(.0212)	(.0213)
Q	.0028***	.0030***	.0047***	.0048***	.0046***	.0047***
	(.0001)	(.0001)	(.0002)	(.0002)	(.0002)	(0002)
σ_U	.0218***	.0351***	.0105***	.0221***	.0111***	.0229***
	(.0014)	(.0018)	(.0014)	(.0017)	(.0013)	(.0017)
shelter83	−.0015***	−.0011***	−.0033***	−.0029***	−.0032***	−.0028***
	(.0001)	(.0001)	(.0002)	(.0002)	(.0002)	(.0002)
Crisis	.0000	−.0002***	−.0004***	−.0000	−.0004***	-.0000
	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)
g_{mb}	.0006		-.0002		−.0003	
	(.0012)		(.0012)		*(.0012)*	
σ_{mb}	−.0203***		.0082***		.0089***	
	(.0038)		(.0036)		(.0035)	
g_{mbr}		−.0221***		−.0202***		−.0212***
		(.0067)		(.0067)		(.0067)
σ_{mbr}		−.5891***		−.3711***		−.3787***
		(.0460)		*(.0451)*		(.0442)
R-squared	.7300	.7314	.7394	.7400	.7397	.7403
Adj R-sq	.7293	.7307	.7388	.7394	.7390	.7397
Obs	44718	44718	44718	44718	44718	44718
Categories	100	100	100	100	100	100

Notes: The standard deviations are in parentheses. *, **, *** - statistically significant at the 10, 5, and 1 per cent. The dependent variable is the standard deviation of the 5-year month-over-month rolling window of each CPI-U subcategory of: inflation, σ^{π}_t. Models use narrow CPI subcategories only, discarding CPI all items and main subcategory aggregates. x_t refers to the average inflation (π_t, π_t^{HP} or π_t). g_{mb} and g_{mbr} are the monthly change of the monetary base and of the M3 index; and σ_{mb} and σ_{mbr} are the standard deviation of the 5-year month-over-month rolling window of each of them.

Table 7: CPI-U Categories.

ELI code	US city average Label	Trade	Q	ini-end
AA	*Apparel	1	1991	entire
AE21	Info. and info. processing	1	1998	1993M1−
AF1	Food	0	none	entire
AF111	Cereals and bakery products	0	none	entire
AF112	Meats, poultry, fish, and eggs	0	none	1967M01−
AF1121	*Meats, poultry, and fish	0	none	entire
AF113	*Fruits and vegetables	1	none	entire
AF1131	Fresh fruits and vegetables	1	none	entire
AF114	Nonalcoh. beverages, beverage materials	0	none	entire
AF115	Other food at home	0	none	1967M01−
AF116	Alcoholic beverages	0	none	1967M01−
AH3	Household furnishings and operations	1	none	1967M01−
AR	Recreation	0	none	1993M1−
EAE	*Footwear	1	1991	entire
EAG	Jewelry and watches	0	none	1986M12−
EEC	Postage and delivery services	0	none	1997M12−
EEE	Information technology, hardw. and serv.	1	1998	1988M12−
EEE02	Computer software and accessories	1	1998	1997M12−
EEE04	Phone hardw.,calcul.,other consumer info items	1	none	1997M12−
EFA	*Cereals and cereal products	0	none	1977M12−
EFA03	Rice, pasta, cornmeal	1	none	1977M12−
EFB	Bakery products	0	none	1977M12
EFB01	Bread	0	none	1997M12−
EFB02	Fresh biscuits, rolls, muffins	0	none	1997M12−
EFB03	Cakes, cupcakes, and cookies	0	none	1978M01−
EFB04	Other bakery products	0	none	1978M01−

ELI code	U.S. city average Label	Trade	Q	ini-end
EFF	Poultry	0	none	entire
EFF01	Chicken	0	none	1997M12–
EFG	Fish and seafood	1	none	entire
EFG01	Fresh fish and seafood	1	none	1997M12–
EFG02	Processed fish and seafood	1	none	1997M12–
EFH	Eggs	0	none	entire
EFJ01	Milk	0	none	1997M12–
EFJ02	Cheese and related products	0	none	1977M12–
EFJ03	Ice cream and related products	0	none	1977M12–
EFK	Fresh fruits	1	none	entire
EFL	Fresh vegetables	1	none	entire
EFM	Processed fruits and vegetables	1	none	1997M12–
EFM02	Frozen fruits and vegetables	0	none	1997M12–
EFM03	Other proc. fruits,vegetables incl. dried	1	none	1997M12–
EFN01	Carbonated drinks	0	none	1978M01–
EFP	Beverage materials incl. coffee, tea	1	none	1997M12–
EFP01	Coffee	1	none	1967M01–
EFP02	Other beverage materials including tea	0	none	1997M12–
EFR	Sugar and sweets	1	none	entire
EFS	Fats and oils	0	none	1967M12–
EFS01	Butter and margarine	0	none	1997M12–
EFS02	Salad dressing	1	none	1997M12–
EFS03	Other fats, oils incl. peanut butter	0	none	1997M12–
EFT01	Soups	1	none	1977M12–
EFT03	Snacks	0	none	1977M12–
EFT04	Spices, seasonings, condiments, sauces	1	none	1978M01–
EFT05	Baby food	1	none	1997M12–
EFV	*Food awayfrom home	0	none	1953M01–
EFW	Alcoholic beverages at home	1	none	1977M12–
EFW02	Distilled spirits at home	1	none	1978M01–

ELI code	U.S. city average Label	Trade	Q	ini-end
EFW03	Wine at home	1	none	1969M01–
EFX	Alcoholic beverages away from home	0	none	1977M12–
EGA	Tobacco and smoking products	0	none	1967M01–
EGC	Personal care services	0	none	1967M01–
EGC01	Haircuts, other personal care serv.	0	none	1997M12–
EGD05	Financial services	0	none	1986M12–
EHA	*Rent of primary residence	0	1994	entire
EHC	Owners' equivalent rent of residences	0	1994	1982M12–
EHD	Tenants' and household insurance	0	1994	1997M12–
EHE	Fuel oil and other fuels	1	none	entire
EHF	Energy services	0	none	entire
EHG	Water-sewer, trash collect. services	0	none	1997M12–
EHH01	Floor coverings	1	none	1997M12–
EHH02	Window coverings	1	none	1997M12–
EHJ	*Furniture and bedding	1	none	1969M01–
EHK01	Major appliances	1	2000M10	1997M12–
EHL01	Clocks, lamps, and decorator items	1	none	1977M12–
EHL03	Dishes and flatware	1	none	1997M12–
EHL04	Electric cookware and tableware	1	none	1997M12–
EHN	*Housekeeping supplies	1	none	1967M01–
EHP01	Domestic services	0	none	1997M12 -
EMC02	Dental services	0	none	1969M01–
EMF01	Prescription drugs	1	none	1969M01–
EMF02	Nonprescription drugs	1	none	2009M12–
EMG	Medical equipment and supplies	1	none	2009M12–

ELI code	U.S. city average Label	Trade	Q	ini-end
ERA01	*Televisions	1	1999	1967M01–
ERA02	Cable and satellite tv serv.	0	1999	1983M12–
ERA04	Video discs,other media,incl.rent.vid.	1	2000	1997M12–
ERA05	*Audio equipment	1	2000	1977M12–
ERD01	*Photographic equipment and supplies	1	2000	1977M12–
ERE01	*Toys	1	none	1977M12–
ERE03	Music instruments and accessories	1	none	1997M12–
ETA01	*New vehicles	1	1992	1953M01–
ETA02	*Used cars and trucks	1	1992	1969M01–
ETB	Motor fuel	1	none	1967M01–
ETC	Motor vehicle parts and equipment	1	none	1977M12–
ETD	Motor vehicle maintenance and repair	0	none	1967M01–
ETE	Motor vehicle insurance	0	none	1969M01–
ETG	Public transportation	0	none	entire
ETG01	Airline fares	1	none	1969M01–
S18064	Prepared salads	0	none	2007M12–
S30021	*Laundry equipment	1	2000M10	1977M12–
S53023	Ship fare	0	none	1997M12–
S61023	Photographic equipment	1	2000	1997M12–
S62054	Veterinarian services	0	none	1997M12–

Sources: BLS, BEA. Series are not seasonally adjusted. Column ini-end indicates the time span the series cover: when the maximum length is covered (1950M01-2020M09), we indicate entire; when ending date is not written, the series ends in 2020M09.
If it is not differently stated, the quality adjustment was introduced in January of the indicated year.

Figures

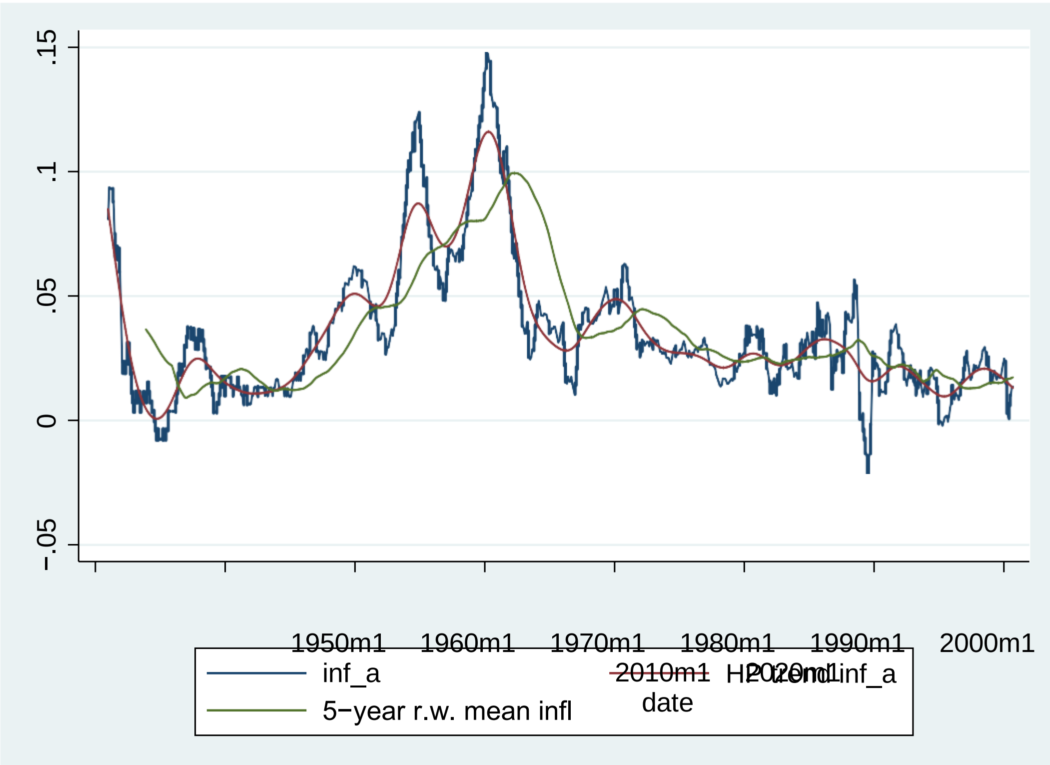

Figure 1: CPI all items.

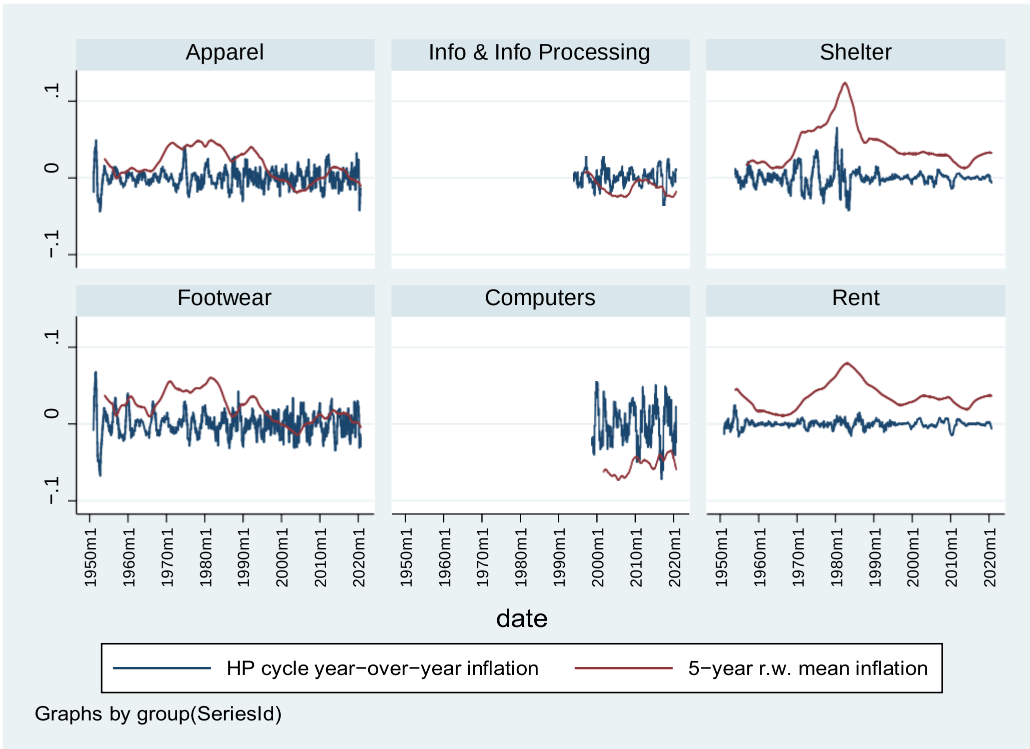

Figure 2: Per-category volatility.

Notes

[1] *See CPI historical changes in https://www.bls.gov/cpi/additional-resources/historical-changes.htm*

[2] *For a short and comprehensive introduction with examples to hedonic price construction and its relevancy in CPI see the Bureau of Labor Statistics (BLS) web-page.*

[3] *We use Stata to test for unknown structural breaks in the logs of total exports and total imports for US and the logs of exports and imports over GDP. The tests report 1973, 1988 and 2008 as breaks.*

[4] *The coefficient for the first lag of the dependent variable is below one, which guarantees its dynamic stability. Moreover, when we introduce a second lag, its coefficient is negative and the sum of both coefficients is below unity.*

[5] *https://www.census.gov/foreign-trade/statistics/historical/index.html*