RELATIVE GOODS' PRICES AND PURE INFLATION

November 2007

Ricardo Reis and Mark W. Watson*

Woodrow Wilson School and Department of Economics, Princeton University
and the National Bureau of Economic Research

ABSTRACT

This paper uses a dynamic factor model for the quarterly changes in consumption goods' prices to separate them into three components: idiosyncratic relative-price changes, aggregate relative-price changes, and changes in the unit of account. The model identifies a measure of "pure" inflation: the common component in goods' inflation rates that has an equiproportional effect on all prices and is uncorrelated with relative price changes at all dates. The estimates of pure inflation and of the aggregate relative-price components allow us to re-examine three classic macro-correlations. First, we find that pure inflation accounts for 15-20% of the variability in overall inflation, so that most changes in inflation are associated with changes in goods' relative prices. Second, we find that the Phillips correlation between inflation and measures of real activity essentially disappears once we control for goods' relative-price changes. Third, we find that, at business-cycle frequencies, the correlation between inflation and money is close to zero, while the correlation with nominal interest rates is around 0.5, confirming previous findings on the link between monetary policy and inflation.

JEL codes: E31, C43, C32
Keywords: Inflation, Relative prices, Dynamic Factor Models, Phillips relation.

*This paper supersedes and significantly elaborates on some parts of our unpublished working paper, Reis and Watson (2007). We are grateful to several colleagues for their valuable input to this research project. For their support and hospitality, Reis thanks the Hoover Institution at Stanford University under a Campbell national fellowship, Columbia University, and the University of Chicago. The National Science Foundation provided support through grant SES-0617811. The data and replication files for this research are at http://www.princeton.edu/~rreis or at http://www.princeton.edu/~mwatson. Contact: rreis@princeton.edu or mwatson@princeton.edu.

1. Introduction

One of the goals of macroeconomics is to explain the aggregate sources of changes in goods' prices. If there was a single consumption good in the world, as is often assumed in models, describing the price changes of consumption would be a trivial matter. But, in reality, there are many goods and prices, and there is an important distinction between price changes that are equiproportional across all goods (absolute-price changes) and changes in the cost of some goods relative to others (relative-price changes). The goal of this paper is to empirically separate these two sources of price changes, and to investigate how they affect the key macroeconomic relations involving inflation.

Our data are the quarterly price changes in each of 187 sectors in the U.S. personal consumption expenditures (PCE) category of the national income and product accounts from 1959:1 to 2006:2. Denoting the rate of price change for the i'th good between dates t-1 and t by π_{it}, and letting π_t be the Nx1 vector that collects these goods' prices, we model their co-movement using a linear factor model:

$$\pi_t = \Lambda F_t + u_t \qquad (1)$$

The k factors in the kx1 vector F_t capture common sources of variation in prices. These might be due to aggregate shocks affecting all sectors, like changes in aggregate productivity, government spending, or monetary policy, or they may be due to shocks that affect many but not all sectors, like changes in energy prices, weather events in agriculture, or exchange rate fluctuations and the price of tradables. The $N\times k$ matrix Λ contains coefficients (or factor loadings) that determine how each individual good's price responds to these shocks. The remainder Nx1 vector u_t captures good-specific relative-price variability associated with idiosyncratic sectoral events or measurement error.

We see the empirical model in (1) as a useful way to capture the main features of the covariance matrix of changes in good's prices. To the extent that the factors in F_t explain a significant share of the variation in the data, then changes in goods prices provide information on the aggregate shocks that macroeconomists care about. We separate this aggregate component of price changes into an absolute-price component and possibly several relative-price components. Denoting these by the scalar a_t and the R_t vector of size $k-1$ respectively, this decomposition can be written as:

$$\Lambda F_t = la_t + \Gamma R_t \tag{2}$$

Absolute price changes affect all prices equiproportionately, so l is an N×1 vector of ones, while relative price changes affect prices in different proportions according to the N×(k−1) matrix Γ. The first question this paper asks is whether the common sources of variation, ΛF_t, can be decomposed in this way.

One issue is that l may not be in the column space of Λ; that is, there may no absolute-price changes in the data. Given estimates of the factor model, we can investigate this empirically using statistical tests and measures of fit. Another issue is that the decomposition in (2) is not unique; that is, a_t and R_t are not separately identified. The key source of the identification problem is easy to see: for any arbitrary (k−1)×1 vector α, we have that $la_t + \Gamma R_t = l(a_t + \alpha' R_t) + (\Gamma - l\alpha')R_t$, so that ($a_t$, R_t) cannot be distinguished from ($a_t + \alpha' R_t$, R_t). The intuition is that the absolute change in prices cannot be distinguished from a change in "average relative prices" $\alpha' R_t$, but there are many ways to define what this average means.[1]

We overcome this challenge by focusing instead on "pure" inflation υ_t, defined as:

$$\upsilon_t = a_t - E[a_t \mid \{R_\tau\}_{\tau=1}^{T}] \tag{3}$$

Pure inflation is identified, and it has a simple interpretation: it is the common component in price changes that has an equiproportional effect on all prices and is uncorrelated with changes in relative prices at all dates. We label it "pure" because, by construction, its changes are uncorrelated with relative-price changes at any point in time. In a simple flexible-price classical model where money is neutral, pure inflation would equal the money growth rate. More generally, it corresponds to the famous thought experiment that economists have used since Hume (1752): "imagine that all prices increase in the same proportion, but no relative price changes."

The first contribution of this paper consists of estimating pure inflation for the post-war United States. These estimates provide an interesting alternative to the history of inflation that is usually told using aggregate inflation measures such as the PCE

[1] One natural way is to assume that relative price changes must add up to zero across all goods. Reis and Watson (2007) use this restriction to define a numeraire price index that measures absolute price changes.

deflator. While the major changes in both measures coincide from the 1960s to the 1980s, they differ markedly in the 1990s. Our method also provides an estimate of the changes in inflation associated with relative price changes. We show how to use these estimates to compute the correlation of inflation with other variables while controlling for relative-price changes.

We then use these estimates to re-examine three classic macroeconomic questions. The first of these is how much of the variability in inflation is accounted for by relative-price changes. Two common ways to estimate this amount have been to look at the contribution of food and energy prices to overall inflation, or to focus on the inflation in a representative median good. Using our more comprehensive approach to control for relative prices, we find that pure inflation accounts for 15-20% of the variability in PCE inflation, and similar results obtain for other standard measures of inflation like the CPI or the GDP deflator. This implies that researchers must be cautious when comparing the predictions for inflation from models with a single consumption good to the data, because most of the variation in standard aggregate inflation indices is associated with relative-price movements, which these models ignore. Moreover, we argue that in models with many goods and nominal rigidities, the 15-20% statistic provides a useful measure to test and distinguish between different models of pricing.

The second relation that we examine is the correlation between inflation and real activity. Phillips (1958) famously first estimated it, and a huge subsequent literature confirmed that it is reasonably large and stable (Stock and Watson, 1999). This correlation has posed a challenge for macroeconomists because it signals that the classical dichotomy between real and nominal variables may not hold. The typical explanation for the Phillips correlation in economic models involves movements in relative prices. For instance, models with sticky wages but flexible goods prices (or vice-versa), explain it by movements in the relative price of labor. Models of the transaction benefits of money or of limited participation in asset markets explain the Phillips correlation by changes in the relative price of consumption today vis-à-vis tomorrow, or asset returns. Models with international trade and restrictions on the currency denomination of prices explain it using the relative price of domestic vis-à-vis foreign goods, or exchange rates. We show that, after controlling for all of these relative prices, the Phillips correlation is still quantitatively and statistically significant. Then, using our

---

A further identification issue in the model is that $\Gamma R_t = \Gamma A A^{-1} R_t$ for arbitrary non-singular matrix A. We estimates, we control instead for the relative price of different goods. This would be suggested by models with many consumption goods, as is the case for instance in modern sticky-price or sticky-information models. We find that, controlling for relative goods prices, the Phillips correlation becomes quantitatively negligible.

The third relation is between monetary policy and inflation, and it is at the center of research in monetary economics. Studies in monetarism have established that in the long run, inflation is tightly linked to money growth, but at the business-cycle frequency, this relation if much weaker. Studies of nominal interest rates have shown that they are also tightly linked to inflation in the long run, but unlike money they strongly correlate with inflation at business-cycle frequencies. We re-examine these facts using pure inflation and controlling for relative goods prices. We find that they still hold: at business-cycle frequencies, inflation is barely correlated with money growth, while it has a correlation of around 0.5 with nominal interest rates.

The paper is organized as follows. Section 2 presents our method to estimate the factor model and to calculate the macroeconomic correlations. Section 3 implements our estimator on the U.S. data and discusses the estimates of pure inflation. Section 4 inspects the three classic macroeconomic relations described above. Section 5 investigates the robustness of the conclusions in the previous two sections to different specifications. Section 6 concludes, summarizing our findings and discussing their implications for theoretical macroeconomic models.

1.1. Relation to the literature

There has been much research on measuring inflation and pure inflation fits into the class of stochastic price indices described in Selvanathan and Rao (1994). Despite this work, as far as we are aware, there have been relatively few attempts at separating absolute from relative-price changes. An important exception is Bryan and Cechetti (1993), who use a dynamic factor model in a panel of 36 price series to measure what we defined above as a_t. They achieve identification and estimate their model imposing very strong and strict assumptions on the co-movement of relative prices, in particular that relative prices are independent across goods. Moreover, while they use their estimates to forecast future inflation, we use them to assess classic macroeconomic relations. [2]

---

can ignore this issue because we do not need to separately identify the elements of R_t.

[2] Bryan, Cecchetti and O'Sullivan (2002) use a version of the Bryan-Cecchetti (1993) model to study the importance of asset prices for an inflation index.

In methods, our use of large-scale dynamic factor models draws on the literature on their estimation by maximum likelihood (e.g., Quah and Sargent, 1993, and Doz, Giannone and Reichlin, 2006) and principal components (e.g., Bai and Ng, 2002, Forni, Hallin, Lippi and Reichlin, 2000, and Stock and Watson, 2002). We provide a new set of questions to apply these methods.

Using these methods on price data, Cristadoro, Forni, Reichlin and Veronesi (2005) estimate a common factor on a panel with price and quantity series and ask a different question: whether it forecasts inflation well. Amstad and Potter (2007) address yet another issue, using dynamic factor models to build measures of the common component in price changes that can be updated daily. Del Negro (2006) estimates a factor model using sectoral PCE data allowing for a single common component and relative price factors associated with durable, non-durable, and services goods sectors. Finally, Altissimo, Mojon, and Zaffaroni (2006) estimate a common factor model using disaggregated Euro-area CPI indices and use the model to investigate the persistence in aggregate Euro-area inflation. The common factor in these papers is not a measure of pure inflation, since it affects different prices differently.

Closer to our paper, in the use of dynamic factor models to extract a measure of inflation that is then used to assess macroeconomic relations suggested by theory, is Boivin, Giannoni and Mihov (2007). They extract a macroeconomic shock using many series that include prices and real quantities, estimate the impulse response of individual prices to this shock, and then compare their shape to the predictions of different models of nominal rigidities. In contrast, we use only price data (and no quantity data) to measure inflation so that we can later ask if it is neutral with respect to quantities. Moreover, we apply our estimates to assess unconditional correlations of real variables with inflation, whereas they focus on the link conditional on identified monetary shocks. Finally, we measure pure inflation, while their inflation measure comes with relative-price movements, so we ask a different set of questions.

2. Measuring pure inflation and calculating macro-correlations

2.1. Estimating pure inflation

The model in (1)-(3) is meant to capture the key properties of the inflation series as they pertain to the estimation of υ_t and the relative-price components, with an eye on the three applications that we discussed in the introduction. We use a factor model for the covariance between shocks because past research focusing on the output of different sectors, and macroeconomic variables more generally, found that this model is able to flexibly account for the main features of the economic data (Stock and Watson, 1989, 2005, Forni et al, 2000).

The strategy for estimating the model can be split in three steps. First, we choose the number of factors (k). Second, we estimate the factors (a_t, R_t) and the factor loadings (Γ), and examine the unit restriction on the loadings in the absolute-price components in (2). Third, we calculate the expectation of absolute-price changes conditional on relative-price changes in (3) and use it to obtain the time-series for pure inflation (υ_t). We discuss each of these in turn.

Choosing the number of factors, that is the size k of the vector F_t, involves a trade-off. On the one hand, a higher k implies that a larger share of the variance in the data is captured by the aggregate components. On the other hand, the extra factors are increasingly harder to reliably estimate and are less quantitatively significant. Bai and Ng (2002) have developed estimators for k that are consistent (as $\min(N,T) \rightarrow \infty$) in models such as this. We compute the Bai-Ng estimators, which are based on the number of dominant eigenvalues of the covariance (or correlation) matrix of the data. We complement them by also looking at a few informative descriptive statistics on the additional explanatory power of the marginal factor. In particular, we estimate an unrestricted version of (1) that does not impose the restriction in (2) that the first factor has a unit loading. We start with one factor and successively increase the number of factors, calculating at each step the incremental share of the variance of each good's inflation explained by the extra factor. If the increase in explained variance is large enough across many goods, we infer it is important to include at least these many factors. These pieces of information lead us to choose a benchmark value for k. In section 5, we investigate the robustness of the results to different choices of k.

To estimate the factor model, we follow two approaches. The first approach estimates (1)-(2) by restricted principal components. It consists of solving the restricted least-squares problem:

$$\min_{\Gamma,(a,R)} \sum_{i=1}^{N} \sum_{t=1}^{T} (\pi_{it} - a_t - \gamma_i' R_t)^2 \tag{4}$$

When N and T are large and the error terms u_{it} are weakly cross-sectionally and serially correlated, the principal components/least squares estimators of the factors have two important statistical properties that are important for our analysis (Stock and Watson, 2002, Bai, 2003, Bai and Ng, 2006). First, the estimators are consistent. Second, the sampling error in the estimated factors is sufficiently small that it can be ignored when the estimates, say $\hat{a}_t$ and $\hat{R}_t$, are used in regressions in place of the true values of a_t and R_t.

The second approach makes parametric assumptions on the stochastic properties of the three latent components (a_t, R_t, and u_{it}) and estimates the model by maximum likelihood. In particular, we assume that (a_t, R_t) follow a vector autoregression, while the u_{it} follow independent autoregressive processes, all with Gaussian errors.[3] The resulting unobserved-components model is:

$$\pi_{it} = a_t + \gamma_i' R_t + u_{it} \tag{5}$$

$$\Phi(L)\begin{pmatrix} a_t \\ R_t \end{pmatrix} = \varepsilon_t \tag{6}$$

$$\rho_i(\mathrm{L})u_{it} = \alpha_i + e_{it} \tag{7}$$

with $\{e_{it}\},\{e_{jt}\}_{j\neq i},\{\varepsilon_t\}$ being mutually and serially uncorrelated sequences that are normally distributed with mean zero and variances $var(e_{it}) = \sigma_i^2$, $var(\varepsilon_t) = Q$. To identify the factors, we use the normalizations that the columns of Γ are mutually orthogonal and add up to zero, although the estimate of υ_t does not depend on this normalization.

Numerically maximizing the likelihood function is computationally complex because of the size of the model. For example, our benchmark model includes a_t and two additional relative price factors, a VAR(4) for (6), univariate AR(1) models for the $\{u_{it}\}$, and N = 187 price series. There are 971 parameters to be estimated.[4] Despite its complexity, the linear latent variable structure of the model makes it amenable to estimation using an EM algorithm with the "E-step" computed by Kalman smoothing and the "M-step" by linear regression. The appendix describes this in more detail. Given

[3] One concern with assuming Gaussianity is that disaggregated inflation rates are skewed and fat-tailed. In general, skewness is not a major concern for Gaussian MLEs in models like this (Watson, 1989), but excess kurtosis is more problematic. To mitigate the problem, we follow Bryan, Cecchetti and Wiggins (1997) and pre-treat the data to eliminate large outliers (section 3 has more details).

parameter estimates, the factors are obtained by signal-extraction.

While this exact dynamic factor model (5)-(7) is surely misspecified − for instance, it ignores small amounts of cross-sectional correlation among the u_{it} terms, conditional heteroskedasticity in the disturbances, and so forth − it does capture the key cross sectional and serial correlation patterns in the data. Doz, Giannone and Reichlin (2006) study the properties of factors estimated from an exact factor structure as in (5)-(7) with parameters estimated by Gaussian MLE, but under the assumption that the data are generated from an approximate factor model (so that (5)-(7) are misspecified). Their analysis shows that when N and T are large, the factor estimates from (5)-(7) behave like the principal-components estimators in the approximate factor model: they are consistent and sampling errors in the estimated factors can be ignored when the estimated factors are used in subsequent regression models. We will use factors estimated from (5)-(7) in our benchmark calculations shown in section 4; results with the principal components estimates of the factors are shown in section 5, which focuses on the robustness of the empirical conclusions.

The model in (1)-(3) imposes the restriction that the loading on the absolute-price factor must be one for all goods. To investigate how restrictive this is, we calculate the increase in fit that comes from dropping the restriction, measured as the fraction of (sample) variance of π_i explained by the factors. Moreover, we estimate the value of θ_i in the N regressions:

$$\pi_{it} = \theta_i a_t + \lambda_i' R_t + u_{it}, \tag{8}$$

using $\hat{a}_t$ and $\hat{R}_t$ in place of a_t and R_t, as explained above. When $\theta_i = 1$, this corresponds to our restricted model, so we can use the estimates of θ_i to judge how adequate is this restriction.

The last step is to compute pure inflation. To evaluate the expectation in (3), we need a model of the joint dynamics of a_t and R_t. As in (6), we model this as a VAR, which is estimated by Gaussian MLE in the parametric factor model, or by OLS using the principal-component estimators for the factors as in the two-step approach taken in factor-augmented VARs (Bernanke, Boivin, Eliasz, 2007). Finally, given estimates of

---

[4]The number of unknown parameters is 186 + 185 (γ_i) + 187 (ρ_i) + 187 (α_i) + 187 ($var(e_i)$) + 36 (Φ) + 3 (var(ε)) = 971, where these values reflect the normalizations used for identification.

$\Phi(L)$, we compute the implied projection in (3) to obtain pure inflation.

2.2. Computing macro-correlations at different frequencies

As described in the introduction, we are interested in the relationship between pure inflation, υ_t, and other macro variables such as the PCE deflator, the unemployment rate, and the rate of growth of money. Let x_t denote one of these macro variables of interest and consider the projection of x_t onto leads and lags of υ_t

$$x_t = \gamma(\mathrm{L})\upsilon_t + e_t. \tag{9}$$

The fraction of variability of x_t associated with $\{\upsilon_t\}$ can be computed as the R^2 from this regression. Adding additional control variables, say z_t, to the regression makes it possible to compute the partial R^2 of x with respect to leads and lags of υ_t after controlling for z_t.

We will compute frequency-domain versions of these variance decompositions and partial R^2's (squared coherences or partial squared coherences). One of their virtues is that they allow us to focus on specific frequency bands, like business cycle frequencies. Another virtue is that they are robust to the filter used to define the variables (e.g., levels or first differences). In particular we report the squared coherence (the R^2 at a given frequency) between x and υ averaged over various frequency bands. When it is relevant, we also report partial squared coherences controlling for (leads and lags) of a vector of variables z (the partial R^2 controlling for z at a given frequency), again averaged over various frequency bands. These various spectral R^2 measures are computed using VAR spectral estimators, where the VAR is estimated using x_t, $\hat{a}_t$, $\hat{R}_t$, and (if appropriate) z_t. The standard errors for the spectral measures are computed using the delta-method constructed from a heteroskedastic-robust estimator for the covariance matrix of the VAR parameters.

3. The U.S. estimates of pure inflation

3.1. The data

The price data are monthly chained price indices for personal consumption expenditures by major type of product and expenditure from 1959:1 to 2006:6. Inflation is measured in percentage points at an annual rate using the final month of the quarter prices: $\pi_{it} = 400\times\ln(P_{it}/P_{it-1})$, where P_{it} are prices for March, June, September, and December.[5] Prices are for goods at the highest available level of disaggregation that have data for the majority of dates, which gives 214 series. We then excluded series with unavailable observations (9 series), more than 20 quarters of 0 price changes (4 series), and series j if there was another series i such that $Cor(\pi_{it}, \pi_{jt}) > 0.99$ and $Cor(\Delta\pi_{it}, \Delta\pi_{jt}) > .99$ (14 series). This left $N = 187$ price series. Large outliers were evident in some of the inflation series, and these observations were replaced with local medians. A detailed description of the data and transformations are given in the appendix.

The level of aggregation, both over time and across goods, affects the interpretation of the results. In the time dimension, if we looked at minute-by-minute price changes it would be hard to believe that there are any equiproportional changes in all prices within one minute. In the goods' dimension, our inflation estimates are "purified" from relative-price changes across sectors, but not within sectors. It is important to keep in mind that our estimates and conclusions are based on quarterly sectoral prices.[6]

One feature of these data is the constant introduction of new goods within each sector (Broda and Weinstein, 2007). Insofar as our statistical factor model of sectoral price changes remains a good description of their co-movement during the sample period, this should not affect our results. Another common concern with price data is the need to re-weight prices to track expenditure shares and measure their effects on welfare. Our model in (1)-(3) does not require any expenditure shares, since the objective of measuring pure inflation is not to measure the cost of living, but rather to separate absolute from relative price changes.

3.2. The number of factors and the order of the autoregressions

Panel (a) of figure 1 shows the largest twenty eigenvalues of the sample correlation matrix. It is clear that there is one large eigenvalue, but it is much less clear how many additional factors are necessary. The Bai-Ng estimates confirm this uncertainty: their ICP_1, ICP_2 and ICP_3 estimates are 2 factors, 1 factor, and 11 factors respectively. Panel (b) of figure 1 summarizes instead the fraction of variance explained

[5] We considered using monthly, rather than quarterly, price changes, but found that the extra idiosyncratic error in monthly price changes outweighed the benefit of more observations.

[6] Most macroeconomic models of inflation are specifed at the quarterly frequency and focus on aggregate or sectoral shocks, so we are not departing from tradition.

by unrestricted factor models with 1 through 4 factors for each of the 187 inflation series.[7] To make the figure easier to read, the series have been ordered by the fraction of variance explained by the 1-factor model. The uncertainty in the appropriate number of factors is evident here as well: the second factor improves the fit for several series, but it is unclear whether a third, fourth or fifth factor is necessary. In our benchmark model we will use 3 factors (a_t and two relative price factors in R_t). We summarize the key results for other choices in section 5.

We use the parametric factor estimates from (5)-(7) in our benchmark calculations, and summarize results from the principal components estimators in Section 5. The VAR for the factors in the benchmark specification uses 4 lags, guided by a few diagnostic tests (not reported). It is well-known that inflation series are quite persistent and it is difficult to reject the null hypothesis that they have a unit root in the autoregressive representation (Pivetta and Reis, 2007). When we estimate the VAR in (6), we find that there are several large roots in $\Phi(L)$ and one that is very close to one. In our benchmark model, we impose two unit roots in $\Phi(L)$; that is, a_t and one of the relative price factors are treated as I(1) processes. Results in which these unit roots are not imposed turn out to be very similar, and we summarize results for these models in section 5. Finally, we use only one lag in the univariate autoregressions of u_{it}, as suggested by diagnostic tests. The estimated roots of $\rho_i(L)$ are typically small, suggesting I(0) variation in the idiosyncratic relative inflation rates.

Values for the estimated parameters for the benchmark model are given in the appendix.

3.3. Estimation results

Panel (a) of figure 2 summarizes the fit of unrestricted factor models that do not impose the unit restriction on the loading of the absolute-price factor. It shows that the increase in fit, measured by R^2 is less than 3% for 80% of the series. The median increase is less than 1%. The unrestricted model appears to fit appreciably better only for a small number of price series: for 10 series the increase in R^2 exceeds 10%. Panel (b) of figure 2 shows the ordered values of the estimates of θ_i, that is the least-squares coefficient from regressing π_{it} on $\hat{a}_t$ controlling for $\hat{R}_t$. Most of the estimates are close to

[7] These measures were computed as $R_i^2 = 1 - [\mathrm{var}(u_i) / s_{\pi_i}^2]$, where $\mathrm{var}(u_i)$ is the estimated variance of u_i

1. Panel (c) shows the ordered values of the (4-lag Newey-West) *t*-statistic testing that θ_i =1. There are far more rejections of the restriction than would be expected by sampling error, with over 30% of the *t*-statistics above the standard 5% critical values and over 20% above the 1% critical values. These results suggest that, as a formal matter, the unit factor loading restriction in (2) appears to be rejected by the data. That said, the results in panels (a) and (b) suggest that little is lost by imposing this restriction.

Figure 3 turns to the more interesting results: the maximum-likelihood estimates of pure inflation. The figure plots estimates of υ_t as well the more familiar core PCE inflation, and inflation in a representative sector, "major household appliances." (The figure shows 2-year changes of the inflation series because these are smoother and easier to interpret than quarter-to-quarter changes.) Pure inflation is somewhat smoother than the other two series, as well as less volatile (note the difference in the scales of the plots). The standard deviation of $\Delta\upsilon_t$ is 0.40 percent, while that of core inflation changes is 1.26% and the median across the 87 price series is 5.8%.

Often, the three measures move together. For example, the two spikes in inflation in the mid and late 1970s are common to all three measures of inflation. Likewise, the disinflation of the early 1980s shows up both in core inflation as well as pure inflation, and it is the largest contraction in pure inflation in the sample. In the 1990s, movements in pure inflation do not match those in core PCE inflation. The disinflation of 1991-92 is particularly pronounced in pure inflation, but not in core inflation and, in the late 1990s and early 2000s, core inflation was low but pure inflation was particularly high.

4. Re-examining three classic macroeconomic correlations

In this section, we apply our estimates of pure inflation and relative-price changes to answer three economic questions: how much of overall inflation is due to pure inflation? What happens to the correlation between inflation and real activity once we control for relative price changes? Are monetary policy variables closely linked to pure inflation?

4.1 Inflation and pure inflation

Table 1 shows the fraction of the variability of overall inflation associated with

implied by the estimated model and $s^2_{\pi_i}$ is the sample variance of π_i.

pure inflation, either averaged over all frequencies or just over business-cycle frequencies. The first row of the table uses the PCE deflator as the measure of overall inflation, and shows that roughly 15% of the movements in the series are accounted for by pure inflation. The second and third row look at two other commonly used measures of overall inflation, the GDP deflator and the Consumer Price Index, and show similar results.

Two common approaches to strip inflation from relative-price movements are to exclude the prices of food and energy or to look at the median inflation across the different sectors. The second section in table 1 shows that these rough attempts at controlling for relative-price changes go in the right direction but remain quite far from excluding all relative-price changes. Core inflation is more closely tied to pure inflation than its headline counterpart, but the squared coherence is still only around 20%-25%. For median CPI inflation, the squared coherence is less than 20%.[8]

The last section of table 1 shows that pure inflation accounts for between 2% and 8% of the overall variability of sectoral inflation rates. As expected, the majority of price movements are due to relative-price shocks, both aggregate and especially idiosyncratic. More surprising and remarkable, changes in the unit of account measured by pure inflation are not negligible even at the individual good's level.

These results have a few implications for macroeconomic models. It is customary to compare the predictions of models with a single good for inflation, with, for example, the data on the PCE deflator. The results in table 1 show that it is dangerous to do so since as much as 85% of the movements in the PCE deflator are driven by changes in the relatives prices of different goods. It might be better to compare the predictions of these models with our estimated series for pure inflation.

The best option would be to consider models with multiple consumption goods. In the literature on nominal rigidities, there are several models with many goods that typically differ on their assumption on how prices are set (see Taylor, 1999, for a survey). The results on table 1 provide a useful statistic to test and distinguish between these different models. To see this, note that different theories of how firms set prices give different answers to the question: is there pure inflation? In the most popular models of nominal rigidities, firms adjust prices infrequently, either keeping them fixed within adjustments (as in Taylor, 1980, Calvo, 1983, or Sheshinski and Weiss, 1977) or following a plan based on outdated information (as in Fischer, 1977, or Mankiw and Reis, 2002). In these simple models, at any date, there are always some prices in the economy that cannot respond to current conditions. Therefore, whatever common shock affects desired prices, only some firms adjust their actual prices leading to a change in relative prices. There is no pure inflation, because it is never the case that all firms change their prices in exactly the same proportion at the same time. If the data we used to estimate pure inflation were on goods prices, then our finding that there is pure inflation would reject these simple models of nominal rigidities.

Our price data is on sectors though, not individual goods. The same logic as in the previous paragraph applies as long as the extent of stickiness of prices is not exactly the same in every sector. If price stickiness was identical in every sector, even though a common shock to desired prices would lead to relative-price changes within sectors, there would be no relative-price changes across sectors, and we would find pure inflation. Away from this knife-edge case, strict models of nominal rigidities would still imply that any common shock to desired prices would lead to relative-price changes and real effects, but no pure inflation.[9]

More sophisticated models of nominal rigidities can generate movements in pure inflation. For instance, in the imperfect-information model of Lucas (1972), changes in the money supply that are announced ex ante are understood by all firms, so all change their prices equiproportionately in response, leading to pure inflation. Likewise, in the sticky-price model of Christiano, Eichenbaum and Evans (2005), where prices may be indexed in between adjustments, it is possible to have movements in pure inflation. In these models, in response to some shocks only some firms adjust leading to changes in relative prices and real quantities, but in response to other shocks all prices adjust and there is pure inflation. The proportion of price variability accounted for by pure inflation provides a quantitative target with which to directly test the price adjustment mechanism in these models.

In summary, simple models of sticky prices or information imply that there is no pure inflation. Our findings reject these models. More sophisticated models of nominal

---

[8] The series for median inflation is available from the Federal Reserve Bank of Cleveland from 1967:2 onwards.

[9] It is also possible that in a finite sample, one might find some pure inflation even though in theory there should be none. Reis and Watson (2007) investigate this hypothesis by simulating data from simple sticky-price and sticky-information models with heterogeneous sectors. They find that, in these models, sampling uncertainty generates on average only between 2% and 7% fractions of inflation variability accounted for by pure inflation, well below our U.S. estimates.

rigidities allow for pure inflation and their predictions on the size of the variance of pure inflation relative to overall inflation are tightly linked to the assumptions on how prices adjust to shocks. Our findings provide a statistic (15%-20%) to test these assumptions.

4.2 The Phillips correlation

One of the most famous correlations in macroeconomics, due to Phillips (1958), relates changes in prices with measures of real activity. The first panel of table 2 displays the Phillips correlation using our measures of squared coherence. At business-cycle frequencies, measuring inflation with the PCE deflator and real activity with GDP, the average squared coherence (R^2) is 0.28, corresponding to a "correlation" of roughly 0.5. The Phillips correlations for industrial production, consumption, employment or the unemployment rate are all similarly large.

The second and third panels in table 2 show that the usual controls for relative prices reduce the strength of this correlation. Controlling for intertemporal relative prices (using short-term interest rates and stock returns), for the relative price of labor and consumption (using real wages), or for the relative price of domestic and foreign goods (using the real exchange rate) cuts the Phillips correlations in approximately half. Still, these correlations remain quantitatively large and statistically significant at the 5% level.

The last panel of table 2 introduces as controls instead the measures of aggregate relative-price movements that we estimated in this paper. Strikingly, the Phillips correlation disappears over business cycle frequencies. The largest squared coherence point estimate is 0.03 and the point estimates are statistically insignificant at the 10% level for all measures of real activity.

As we saw earlier, the PCE deflator is a noisy measure of inflation, and this may attenuate the Phillips correlation. Table 3 reassesses the Phillips correlations controlling for goods' relative prices by using instead our estimate of pure inflation. Panel (a) shows the squared coherence between υ_t and the measures of real activity, and panels (b) and (c) add the additional controls associated with real wages, asset prices and exchange rates. Evidently, the correlation of the real variables and pure inflation is much smaller than their correlation with the PCE deflator (the squared coherences fall by a factor of roughly two-thirds).

The results in these tables suggest that a large part of the Phillips correlation, that has puzzled macroeconomists for half a century, is driven by changes in good's relative prices. Changes in the unit of account, as captured by pure inflation, do not seem to affect real variables, consistent with the absence of money illusion. However, note that a few of the estimates in table 3 are statistically significant, even if small. This suggests that some money illusion may be present, although it seems to explain very little of the variability of real activity.

4.3 Pure inflation and monetary policy

Another famous set of correlations in empirical macroeconomics are between measures of monetary policy and inflation. Friedman and Schwartz (1963) famously observed that in the long run, money growth and inflation are tightly linked. Equally famously, Fisher (1930) and many that followed showed that there is an almost as strong link between nominal interest rates and inflation in the long run. At business-cycle frequencies though, these correlations are much weaker. The correlation between money growth and inflation is unstable and typically low (Stock and Watson, 1999), while the correlation between inflation and nominal interest rates is typically higher, but well below its level at lower-frequencies (Mishkin, 1992).

Table 4 reproduces the findings described in the previous paragraph for different measures of money growth (M0, M1, and M2) and different short-term nominal interest rates (the federal funds rate and the 3-month Treasury bill rate), measuring inflation using the PCE deflator. The growth rate of M0 and M1 is very weakly correlated with the PCE deflator, and while the relation with M2 is stronger, it is imprecisely estimated. The link between inflation and nominal interest rates is stronger, in particular at business-cycle frequencies.

Table 5 looks at the same set of correlations, but now using pure inflation. The correlation between money growth and pure inflation is very close to zero for all measures. The correlation between nominal interest rates and pure inflation is significantly higher and statistically significant at conventional significance levels, although it is lower than the correlation with PCE inflation.

Therefore, measuring pure inflation and controlling for relative prices does not, by itself, explain why the link between measures of monetary policy is weak in the short-run and strong in the long-run. The results in table 5 show that the two usual measures of the stance of monetary policy only account for a modest amount of the variability in pure inflation. This leaves open the question of what drives changes in the unit of account in the United States.[10]

5. The robustness of the results

Table 6 investigates the robustness of the key empirical conclusions to four aspects of the model specification: (i) the number of estimated factors, (ii) the method for estimating the factors (signal extraction using the parametric factor model (5)-(7) versus principal components on (4)), (iii) the imposition of unit roots in the factor VAR for the parametric model, and (iv) the number of lags and imposition of unit roots in the VAR spectral estimator used to compute the various coherence estimates.

The first row of the table shows results for the benchmark model, where the first column provides details of the factor estimates and where "(1,1,0)" denotes a parametric k=3 factor model where the first and second factor are I(1) processes and the third is I(0). The next column, labeled "VAR", summarizes the specification of the VAR used to compute the spectral estimates, which for the benchmark model involves 4 lags of first differences (D,4) of υ_t and, for the final two columns, first differences of money growth and interest rates. The next set of results are for factor models estimated using the parametric model, but with different numbers of factors and/or I(0) specifications for the first two factors. Results are shown for spectral estimates computed using the first-difference VAR and for a VAR computed using the level of υ_t and, for the final two columns, the level of money growth and nominal interest rates. The final rows of the table show results for factors computed using principal components. The numerical entries in the table are the average squared coherence of the estimate of υ_t with the variable listed in column heading (in the case of real GDP, controlling for interest rates, stock returns and wages as in the panel (b) of table 3).

Looking across the entries in the table, two results stand out. First, the quantitative conclusions concerning the correlation of υ_t with aggregate inflation (core PCE in the table), real output (real GDP in the table) and monetary policy indicators (M2 and the nominal Federal Funds rate in the table) appear to be quite robust across the different specifications. Second, the various estimates of υ_t based on the parametric model are highly correlated with the estimates from the benchmark model, but the

[10] An alternative perspective works in reverse order. If υ_t accurately measures pure inflation, and since many models predict that it is determined by monetary policy, then the estimates of υ_t may be used as an indicator of the stance of monetary policy.

estimates based on principal components are less so. The R^2 measures relating the principal components estimates of υ_t and the benchmark estimates range from 0.38 to 0.66, suggesting correlations in the range of 0.6 to 0.8. Figure 4 shows the estimates of $\upsilon_t - \upsilon_{t-8}$ from the benchmark model (this is the same series plotted in figure 3) and the principal components estimates constructed from the corresponding 3-factor model. While the two series evolve similarly (their correlation is 0.65), there are some obvious differences. Our interpretation of these differences is that, despite their shared large N,T consistency properties, there is some gain from exploiting the time series averaging used in the parametric model that is ignored in the principal components estimator. In any event, despite the differences in the two sets of estimates for pure inflation, their implications for the macroeconomic correlations summarized in the remaining columns of the table are similar.

6. What have we done and why does it matter?

In this paper, we decomposed the quarterly change in sectoral goods' prices into three components: pure inflation, aggregate relative prices, and idiosyncratic relative prices. We used different estimation techniques and specifications to robustly estimate pure inflation, and proposed a simple method to compute macroeconomic correlations while controlling for goods' relative price changes.

Our first finding was that pure inflation can differ markedly from other conventional measures of inflation, like the PCE deflator or its core version. It is smoother, less volatile, and in particular in the 1990s, its ups-and-downs are quite different from those in other measures of inflation. This should be useful to economic historians since it provides an alternative account of the movements in inflation in the last half-century. Relative to existing measure of inflation, pure inflation has the virtue of separating absolute from relative-price changes, which is a crucial distinction in economic theory. Moreover, pure inflation matches more closely the concept that many economists seem to have in mind when discussing aggregate movements in prices and monetary policy (typically based on intuition that comes from a one-good world).

Our second main finding was that pure inflation was quantitatively significant (it accounts for about 5% of individual price changes), but only accounts for 15-20% of the variability in inflation measured by conventional price indices, like the PCE deflator, the GDP deflator, or the CPI. This has at least two implications for the work of economic theorists building models to explain inflation. First, it shows that comparing the predictions of one-good models with common measures of inflation is flawed. The difference between these measures and pure inflation is large enough that it can easily lead to mistakenly accepting or rejecting models. Second, our estimates provide a new test statistic with which to test the pricing assumptions of models with many goods. An important ingredient (and topic of debate) in recent models of nominal rigidities is a model of pricing that implies slow adjustment of prices to monetary policy shocks together with frequent price changes. The fraction of the variability of cost-of-living inflation accounted for by pure inflation can be an important statistic to diagnose the success of these models at fitting the data.

Third, we found that, once we controlled for relative goods' prices, the Phillips correlation became quantitatively insignificant. Therefore, the correlation between real quantity variables and nominal inflation variables that we observe in the data can be accounted for by changes in relative prices. This implies that models that break the classical dichotomy via nominal rigidities in good's price adjustment are likely more promising than models that rely on money illusion on the part of agents.

Fourth, we found that pure inflation is partly related to monetary policy variables. The link to the growth rate in monetary aggregates is weak, but the correlation with nominal interest rates at business cycle frequencies is strong (approximately 0.5).

To conclude, economic theories have strong predictions on whether and when there should be pure inflation and what its effects would be, and discussions of monetary policy often revolve around its relation with pure inflation. However, observing pure inflation is naturally difficult, since the concept itself is more a fruit of thought experiments than something easily observed. As a result, there have been few systematic attempts to measure it in the data. The goal of this paper was to make some progress on measuring pure inflation and understanding its effects. Our estimates are certainly not perfect. We hope, however, that they are sufficiently accurate that future research can look deeper into the time-series and the moments that we provide, and that by stating the challenges and putting forward a benchmark, we can motivate future research to come up with better estimators. Likewise, we are sure that our findings will not settle the debates around the key macroeconomic correlations. Our more modest hope is that they offer a new perspective on how to bring data to bear on these long-standing questions.

References

Altissimo, Filippo, Benoit Mojon, and Paolo Zaffaroni (2006). "Fast Micro and Slow Macro: Can Aggregation Explain the Persistence of Inflation?" Manuscript, Federal Reserve Bank of Chicago.

Amstad, Marlene and Simon M. Potter (2007). "Real Time Underlying Inflation Gauges for Monetary Policy Makers." Manuscript, Federal Reserve Bank of Chicago.

Bai, Jushan (2003). "Inferential Theory for Factor Models of Large Dimensions." *Econometrica*, vol. 71 (1), pp. 135-171.

Bai, Jushan and Serena Ng (2002). "Determining the Number of Factors in Approximate Factor Models." *Econometrica*, vol. 70 (1), pp. 191-221.

Bai, Jusham and Serena Ng (2006). "Confidence Intervals for Diffusion Index Forecasts and Inference for Factor Augmented Regressions." *Econometrica*, 74:4, p. 1133-1150.

Bernanke, Ben , Jean Boivin and Piotr S. Eliasz (2005). "Measuring the Effects of Monetary Policy: A Factor-augmented Vector Autoregressive (FAVAR) Approach." *Quarterly Journal of Economics*, vol. 120 (1), pp. 387-422.

Boivin, Jean, Marc Giannoni and Ilian Mihov (2007). "Sticky Prices and Monetary Policy: Evidence from Disaggregated Data." NBER working paper 12824.

Broda, Christian and David Weinstein (2007). "Product Creation and Destruction: Evidence and Price Implications" NBER working paper 13041.

Bryan, Michael F. and Stephen G. Cecchetti (1993). "The Consumer Price Index as a Measure of Inflation." Federal Reserve Bank of Cleveland Economic Review, pp. 15-24.

Bryan, Michael F., Stephen G. Cecchetti and Rodney L. Wiggins II (1997). "Efficient Inflation Estimation." NBER working paper 6183.

Calvo, Guillermo (1983). "Staggered Prices in a Utility-Maximizing Framework." *Journal of Monetary Economics*, vol. 12, pp. 383-398.

Christiano, Lawrence J., Martin Eichenbaum, and Charles S. Evans (2005). "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy." *Journal of Political Economy*, vol. 113 (1), pp. 1-45.

Cristadoro, Riccardo, Mario Forni, Lucrezia Reichlin and Giovanni Veronese (2005). "A Core Inflation Index for the Euro Area." *Journal of Money, Credit and Banking*, vol. 37 (3), pp. 539-560.

Del Negro, Marco (2006). "Signal and Noise in Core PCE." presentation, Federal Reserve Bank of Atlanta, June 2006.

Doz, Catherine, Domenico Giannone and Lucrezia Reichlin (2006). "A Quasi Maximum Likelihood Approach for Large Dynamic Factor Models." CEPR discussion paper 5724.

Fischer, Stanley (1977). "Long-Term Contracts, Rational Expectations, and the Optimal Money Supply Rule." *Journal of Political Economy*, vol. 85 (1), pp. 191-205.

Fisher, Irving (1930). *The Theory of Interest*. MacMillan, New York.

Forni, Mario, Marc Hallin, Marco Lippi, and Lucrezia Reichlin (2000). "The Generalized Dynamic Factor Model: Identification and Estimation." *Review of Economics and Statistics*, vol. 82 (4), pp. 540-554.

Friedman, Milton and Anna J. Schwartz (1963). *A Monetary History of the United States.* Princeton: Princeton University Press.

Hamilton, James D. (1993). *Time Series Analysis*, Princeton: Princeton University Press.

Hume, David (1752). *Political Discourses*. Reprinted in "Essays, Moral, Political, and Literary" edited by Eugene F. Miller, Liberty Fund.

Lucas, Robert E., Jr. (1972). "Expectations and the Neutrality of Money." *Journal of Economic Theory*, vol. (4), pp. 103-124.

Mankiw, N. Gregory and Ricardo Reis (2002). "Sticky Information versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve." *Quarterly Journal of Economics*, vol. 117 (4), pp. 1295-1328.

Mishkin, Frederic S. (1992). "Is the Fisher Effect for Real? A Reexamination of the Relationship between Inflation and Interest Rates." *Journal of Monetary Economics*, vol. 30 (2), pp. 195-215.

Phillips, Alban W. H. (1958). "The Relation between Unemployment and the Rate of Change of Money Wage Rates in the United Kingdom, 1861-1957." *Economica*, vol. 25 (2), pp. 283-299.

Pivetta, Frederic and Ricardo Reis (2007). "The Persistence of Inflation in the United States." *Journal of Economic Dynamics and Control*, vol. 31 (4), pp. 1326-1358.

Quah, Danny and Thomas J. Sargent (1993). "A Dynamic Index Model for Large Cross-Sections." In James H. Stock and Mark W. Watson, eds., *Business Cycles, Indicators, and Forecasting*, pp. 161–200, Chicago: University of Chicago Press and NBER.

Reis, Ricardo and Mark W. Watson (2007) "Measuring Changes in the Value of the Numeraire." Manuscript, Princeton University.

Selvanathan, E. A. and D. S. Prasada Rao (1994). *Index Numbers: A Stochastic Approach*. Michigan: University of Michigan Press.

Sheshinski, Eytan and Yoram Weiss (1977). "Inflation and Costs of Price Adjustment." *Review of Economic Studies*, vol. 44 (2), pp. 287-303.

Shumway, Robert H. and David S. Stoffer (1982). "An Approach to Time Series Smoothing and Forecasting using the EM Algorithm." *Journal of Time Series Analysis*, vol. 2, pp. 253-264.

Stock, James H. and Mark W. Watson (1989). "New Indexes of Leading and Coincident Indicators." In Olivier J. Blanchard and Stanley Fischer, eds., *NBER Macroeconomics Annual 1989*, pp. 351-394.

Stock, James H. and Mark W. Watson (1999). "Business Cycle Fluctuations in U.S. Macroeconomic Time Series." In John B. Taylor and Michael Woodford, eds., *Handbook of Macroeconomics*, Elsevier..

Stock, James H. and Mark W. Watson (2002). "Forecasting Using Principal Components from a Large Number of Predictors." *Journal of the American Statistical Association*, vol. 97, 1167-1179.

Stock, James H. and Mark W. Watson (2005). "Implications of Dynamic Factor Models for VAR Analysis." NBER working paper 11467.

Taylor, John B. (1980). "Aggregate Dynamics and Staggered Contracts." *Journal of Political Economy*, vol. 88 (1), pp. 1-24.

Taylor, John B. (1999). "Staggered Price and Wage Setting in Macroeconomics." In John B. Taylor and Michael Woodford, *Handbook of Macroeconomics*, Elsevier.

Watson, Mark W. (1989). "Recursive Solution Methods for Dynamic Linear Rational Expectations Models." *Journal of Econometrics*, vol. 41, pp. 65-91.

Watson, Mark W. and Robert F. Engle (1983). "Alternative Algorithms for the Estimation of Dynamic Factors, MIMIC, and Varying Coefficient Regression models." *Journal of Econometrics*, vol. 23, pp. 385-400.

Appendix

All price series are from NIPA Table 2.4.4U available from http://www.bea.gov/national/nipaweb/nipa_underlying/SelectTable.asp. Quarterly inflation rates were computed using the first difference of logarithms of the price indices for the last month of the quarter. Inflation observations that differed from the series median by more that six times the interquartile range were replaced by the local median computed using the six adjacent observations. The table below shows the price index from the NIPA table, the series description, the standard deviation of the (outlier-adjusted) series over 1959:2-2006:2 and the 2005 PCE expenditure share. To save space, the final four columns of this table are used to show the estimated parameters from the benchmark 3-factor model.

Table A1: Series Descriptions, Summary Statistics, and Parameter Estimates from the Benchmark 3-factor Model

Num.	Label	Description	s_π	2005 Share	Benchmark Model Parameters			
					λ_1	λ_2	ρ	σ_e
001	P1NFCG D	New foreign autos	4.5	0.5	1.14	0.00	-0.13	0.88
002	P1NETG D	Net transactions in used autos	1.8	0.4	2.35	0.42	0.15	2.71
003	P1MARG D	Used auto margin	6.9	0.3	1.09	0.18	0.02	4.22
004	P1REEG D	Employee reimbursement	7.5	0.0	1.11	0.15	-0.19	1.68
005	P1TRUG D	Trucks, new and net used	4.8	2.4	1.25	-0.09	-0.12	0.96
006	P1TATG D	Tires and tubes	5.8	0.3	0.15	0.57	0.12	1.27
007	P1PAAG D	Accessories and parts	5.5	0.4	-0.21	-0.04	0.26	1.15
008	P1FNRG C	Furniture, incl. matt. and bedsprings	4.1	0.9	0.53	0.30	-0.29	0.77
009	P1MHAG D	Major household appliances	4.0	0.4	0.84	0.13	0.09	0.73
010	P1SEAG D	Small electric appliances	5.0	0.1	1.06	0.35	0.12	0.93
011	P1CHNG C	China, glassware, tableware, and utensil	6.7	0.4	1.32	0.93	-0.28	1.25
012	P1TVSG D	Television receivers	5.4	0.2	1.16	0.47	0.42	0.99
013	P1AUDG D	Audio equipment	5.2	0.3	0.57	0.06	-0.17	1.17
014	P1RTDG D	Records, tapes, and disks	4.9	0.2	-0.21	0.07	-0.06	1.17
015	P1MSCG D	Musical instruments	4.0	0.1	0.41	0.22	-0.13	0.85
016	P1FLRG D	Floor coverings	5.8	0.2	0.60	0.09	-0.24	1.27
017	P1CLFG D	Clocks, lamps, and furnishings	6.0	0.4	1.22	0.45	-0.04	1.29
018	P1TEXG D	Blinds, rods, and other	8.6	0.1	1.54	1.07	-0.28	1.81
019	P1WTRG D	Writing equipment	5.1	0.0	0.18	-1.01	-0.28	1.06
020	P1HDWG D	Tools, hardware, and supplies	4.7	0.1	0.56	0.14	-0.04	1.05
021	P1LWNG D	Outdoor equipment and supplies	5.1	0.0	0.73	0.13	-0.16	1.11
022	P1OPTG C	Ophth. prd, and orthopedic appliances	2.8	0.3	0.29	-0.05	-0.07	0.55
023	P1CAMG D	Photographic equipment	6.0	0.1	1.26	0.04	0.34	1.25
024	P1BCYG D	Bicycles	4.3	0.1	-0.09	0.30	-0.15	0.90
025	P1MCYG D	Motorcycles	4.7	0.2	1.18	-0.11	0.01	1.00
026	P1AIRG D	Pleasure aircraft	7.2	0.0	0.05	0.57	0.06	1.64
027	P1JRYG C	Jewelry and watches (18)	7.3	0.7	0.15	0.33	-0.21	1.67
028	P1BKSG C	Books and maps (87)	5.8	0.5	1.00	-0.37	-0.25	1.23
029	P1GRAG D	Cereals	6.3	0.4	-1.34	-0.19	0.45	1.34
030	P1BAKG D	Bakery products	4.6	0.6	-0.22	0.25	0.14	1.01
031	P1BEEG D	Beef and veal	13.0	0.4	-4.16	-0.28	-0.16	2.88
032	P1PORG D	Pork	6.9	0.3	-3.52	-0.91	0.19	3.96
033	P1MEAG D	Other meats	8.3	0.2	-2.72	-0.74	0.17	1.84
034	P1POUG D	Poultry	7.0	0.5	-2.23	0.03	-0.20	4.06
035	P1FISG D	Fish and seafood	5.7	0.2	-0.69	0.01	0.18	1.22
036	P1GGSG D	Eggs	7.4	0.1	-5.34	-0.42	-0.03	6.63
037	P1MILG D	Fresh milk and cream	6.9	0.2	-1.10	0.04	-0.03	1.63
038	P1DAIG D	Processed dairy products	6.2	0.5	-1.19	0.08	0.28	1.32
039	P1FRUG D	Fresh fruits	4.5	0.3	-0.89	0.21	-0.07	3.55
040	P1VEGG D	Fresh vegetables	9.3	0.4	-2.70	-0.21	-0.41	6.59
041	P1PFVG D	Processed fruits and vegetables	5.7	0.2	0.40	0.15	0.38	1.21
042	P1JNBG D	Juices and nonalcoholic drinks	6.4	0.8	0.16	0.64	0.32	1.22
043	P1CTMG D	Coffee, tea and beverage materials	1.8	0.2	1.49	0.89	0.58	2.31
044	P1FATG D	Fats and oils	9.3	0.1	-0.60	1.33	0.52	1.71
045	P1SWEG D	Sugar and sweets	6.3	0.5	-0.97	0.36	0.27	1.37
046	P1OFDG D	Other foods	4.1	1.3	0.11	0.05	0.11	0.76

047	P1PEFG D	Pet food	3.9	0.3	-0.19	0.04	-0.04	0.79
048	P1MLTG D	Beer and ale, at home	3.6	0.7	0.42	0.18	0.13	0.66
049	P1WING D	Wine and brandy, at home	3.9	0.2	-0.51	0.14	-0.02	0.79
050	P1LIQG D	Distilled spirits, at home	2.1	0.2	-0.17	-0.40	0.25	0.54
051	P1OPMG D	Other purchased meals	2.8	4.5	-0.15	0.09	0.30	0.32
052	P1APMG C	Alcohol in purchased meals	3.7	0.6	0.45	-0.06	-0.16	0.79
053	P1MFDG D	Food supplied military	3.0	0.0	-0.20	0.10	0.25	0.40
054	P1FFDG C	Food produced and consumed on farms	0.9	0.0	-4.86	-1.37	-0.09	4.98
055	P1SHUG C	Shoes (12)	3.8	0.6	-0.01	0.41	0.01	0.78
056	P1WGCG D	Clothing for females	4.5	1.8	-0.14	0.30	0.02	1.10
057	P1WICG D	Clothing for infants	8.9	0.1	1.40	0.58	-0.33	1.88
058	P1MBCG D	Clothing for males	3.5	1.2	0.30	0.34	0.11	0.74
059	P1MSGG D	Sewing goods for males	6.4	0.0	0.28	0.25	-0.29	1.46
060	P1MUGG D	Luggage for males	2.6	0.0	1.29	1.25	-0.21	2.82
061	P1MICG C	Std. clothing issued to military personnel	2.8	0.0	0.28	0.16	0.15	0.43
062	P1GASG D	Gasoline and other motor fuel	4.2	3.2	-6.30	1.54	-0.13	5.37
063	P1LUBG D	Lubricants	5.5	0.0	-0.37	0.47	0.37	1.09
064	P1OILG D	Fuel oil	3.7	0.1	-7.75	2.55	0.21	4.84
065	P1FFWG D	Farm fuel	6.0	0.0	-3.91	1.84	0.14	3.38
066	P1TOBG C	Tobacco products	7.5	1.0	0.36	-0.70	0.06	1.83
067	P1SOAG D	Soap	4.9	0.1	1.21	0.25	-0.13	0.92
068	P1CSMG D	Cosmetics and perfumes	4.3	0.2	1.07	0.17	-0.24	0.78
069	P1SDHG C	Semidurable house furnishings	7.4	0.5	1.76	0.64	-0.44	1.40
070	P1CLEG D	Cleaning preparations	4.2	0.4	0.66	0.13	0.09	0.75
071	P1LIGG D	Lighting supplies	7.2	0.1	0.87	0.53	-0.13	1.59
072	P1PAPG D	Paper products	5.6	0.3	0.36	0.40	0.04	1.17
073	P1RXDG D	Prescription drugs	4.0	2.6	0.33	-0.62	0.67	0.55
074	P1NRXG D	Nonprescription drugs	4.0	0.3	0.91	-0.45	0.10	0.64
075	P1MDSG D	Medical supplies	3.7	0.1	0.77	-0.58	-0.13	0.64
076	P1GYNG D	Gynecological goods	4.2	0.0	1.02	0.24	-0.08	0.68
077	P1DOLG D	Toys, dolls, and games	5.4	0.6	1.04	0.47	0.10	1.08
078	P1AMMG D	Sport supplies, including ammunition	4.7	0.2	0.35	0.15	-0.16	1.06
079	P1FLMG D	Film and photo supplies	4.6	0.0	0.62	-0.25	0.10	1.06
080	P1STSG D	Stationery and school supplies	4.7	0.1	0.91	0.50	-0.04	0.95
081	P1GREG D	Greeting cards	4.8	0.1	0.92	0.50	-0.04	0.97
082	P1ABDG C	Expenditures abroad by U.S. residents	16.8	0.1	0.28	0.54	0.18	4.02
083	P1MGZG D	Magazines and sheet music	5.5	0.3	0.66	-0.44	-0.31	1.17
084	P1NWPG D	Newspapers	3.8	0.2	0.87	0.24	0.14	0.78
085	P1FLOG C	Flowers, seeds, and potted plants	6.7	0.2	0.57	0.29	-0.12	1.54
086	P1OMHG D	Owner occupied mobile homes	2.5	0.4	0.03	-0.74	-0.30	0.24
087	P1OSTG D	Owner occupied stationary homes	2.4	10.7	0.00	-0.75	-0.17	0.19
088	P1TMHG D	Tenant occupied mobile homes	3.8	0.1	0.07	-0.75	-0.26	0.77
089	P1TSPG D	Tenant occupied stationary homes	2.4	2.8	-0.04	-0.77	-0.31	0.17
090	P1TLDG D	Tenant landlord durables	3.8	0.1	0.45	-0.51	0.25	0.66
091	P1FARG C	Rental value of farm dwellings (26)	4.3	0.2	-0.27	-0.15	0.70	0.84
092	P1HOTG D	Hotels and motels	6.3	0.6	0.19	-0.01	-0.10	1.38
093	P1HFRG D	Clubs and fraternity housing	2.9	0.0	0.03	-0.65	-0.33	0.43
094	P1HHEG D	Higher education housing	3.0	0.2	-0.15	-0.78	0.04	0.54
095	P1HESG D	El. and secondary education housing	8.9	0.0	0.16	-0.84	-0.36	2.01
096	P1TGRG D	Tenant group room and board	3.4	0.0	-0.12	-0.70	-0.38	0.60
097	P1ELCG C	Electricity (37)	5.7	1.5	0.43	-0.16	0.23	1.15
098	P1NGSG C	Gas (38)	2.6	0.8	0.35	0.19	0.44	2.71
099	P1WSMG D	Water and sewerage maintenance	3.9	0.6	0.88	-0.50	0.20	0.75
100	P1REFG D	Refuse collection	4.1	0.2	1.02	-0.56	0.29	0.75
101	P1LOCG D	Local and cellular telephone	4.5	1.3	0.41	-0.84	0.05	0.98
102	P1OLCG D	Local telephone	4.4	0.6	0.05	-1.00	0.00	1.00
103	P1LDTG D	Long distance telephone	5.3	0.3	0.15	-0.31	0.33	1.24
104	P1INCG D	Intrastate toll calls	5.1	0.1	-0.08	-0.66	0.36	1.17
105	P1ITCG D	Interstate toll calls	6.3	0.2	0.38	0.09	0.23	1.52
106	P1DMCG D	Domestic service, cash	4.3	0.2	0.27	0.10	0.24	0.98
107	P1DMIG D	Domestic service, in kind	6.0	0.0	-1.76	-0.21	-0.03	1.24
108	P1MSEG D	Moving and storage	3.7	0.2	0.15	0.09	-0.03	0.69
109	P1FIPG D	Household insurance premiums	3.7	0.2	0.13	-0.49	0.32	0.84
110	P1FIBG D	Less: Household insurance benefits paid	3.3	0.1	0.86	0.38	-0.28	0.40
111	P1RCLG D	Rug and furniture cleaning	4.4	0.0	0.33	0.06	-0.36	0.79
112	P1EREG D	Electrical repair	3.8	0.1	0.06	0.12	0.17	0.79
113	P1FREG D	Reupholstery and furniture repair	3.2	0.0	-0.11	-0.20	0.13	0.74
114	P1MHOG D	Household operation services, n.e.c.	3.7	0.2	0.03	0.09	-0.02	0.73
115	P1ARPG D	Motor vehicle repair	2.9	1.7	0.17	0.06	0.30	0.34
116	P1RLOG D	Motor vehicle rental, leasing, and other	4.9	0.6	0.82	0.15	-0.16	0.96
117	P1TOLG C	Bridge, tunnel, ferry, and road tolls	6.2	0.1	0.00	-0.75	-0.19	1.42

118	P1AING C	Insurance	4.2	0.7	0.84	-0.73	0.13	3.61
119	P1IMTG C	Mass transit systems	5.4	0.1	0.09	-0.45	0.09	1.35
120	P1TAXG C	Taxicab	5.7	0.0	0.05	0.22	0.02	1.27
121	P1IBUG C	Bus	9.2	0.0	-0.10	-0.37	-0.20	2.13
122	P1IAIG C	Airline	15.0	0.4	-0.64	0.75	-0.04	3.60
123	P1TROG C	Other	9.1	0.1	-0.23	-0.04	-0.05	2.11
124	P1PHYG C	Physicians	3.3	4.0	0.63	-0.09	0.50	0.42
125	P1DENG C	Dentists	2.7	1.0	0.39	-0.22	0.17	0.48
126	P1OPSG C	Other professional services	3.2	2.7	0.61	0.04	0.25	0.50
127	P1NPHG C	Nonprofit	3.1	4.4	0.05	-0.02	0.03	0.48
128	P1GVHG C	Government	4.3	1.4	-0.10	-0.06	0.51	0.76
129	P1NRSG C	Nursing homes	3.3	1.3	0.05	0.11	-0.30	0.62
130	P1MING C	Medical care and hospitalization	0.3	1.4	-0.90	-0.95	0.29	4.89
131	P1IING C	Income loss	5.7	0.0	0.70	-1.74	0.64	4.86
132	P1PWCG C	Workers' compensation	8.1	0.2	-0.55	0.26	0.80	1.16
133	P1MOVG C	Motion picture theaters	4.1	0.1	0.05	0.08	0.15	1.07
134	P1LEGG C	Leg. theaters and opera,	4.2	0.1	0.13	0.11	0.16	1.10
135	P1SPEG C	Spectator sports	4.1	0.2	-0.15	-0.34	-0.08	1.03
136	P1RTVG C	Radio and television repair	3.1	0.1	0.28	-0.52	0.33	0.62
137	P1CLUG C	Clubs and fraternal organizations	4.2	0.3	-0.13	0.42	-0.27	0.77
138	P1SIGG D	Sightseeing	5.3	0.1	0.04	0.00	-0.07	1.21
139	P1FLYG D	Private flying	9.8	0.0	0.48	0.19	-0.28	2.27
140	P1BILG D	Bowling and billiards	4.1	0.0	0.46	-0.31	0.05	0.96
141	P1CASG D	Casino gambling	2.9	0.9	-0.28	0.10	-0.22	0.32
142	P1OPAG D	Other com. participant amusements	2.8	0.3	0.27	0.06	0.16	0.59
143	P1PARG C	Pari-mutuel net receipts	4.8	0.1	-0.66	-0.09	0.51	0.99
144	P1PETG D	Pets and pets services excl. vet.	3.6	0.1	-0.12	-0.07	0.00	0.76
145	P1VETG D	Veterinarians	3.0	0.2	-0.18	-0.23	0.13	0.67
146	P1CTVG D	Cable television	7.0	0.7	0.18	-0.21	0.08	1.76
147	P1FDVG D	Film developing	3.8	0.1	0.76	-0.08	0.39	0.85
148	P1PICG D	Photo studios	3.8	0.1	0.12	-0.12	0.09	0.89
149	P1CMPG D	Sporting and recreational camps	3.4	0.0	0.09	-0.04	-0.07	0.81
150	P1HREG D	High school recreation	4.7	0.0	0.05	-0.14	-0.22	1.12
151	P1NECG D	Commercial amusements n.e.c.	3.4	0.6	0.25	0.00	-0.05	0.80
152	P1NISG D	Com. amusements n.e.c. except ISPs	3.3	0.4	0.12	-0.05	-0.04	0.80
153	P1SCLG D	Shoe repair	3.3	0.0	0.04	-0.27	0.12	0.64
154	P1DRYG D	Drycleaning	3.6	0.1	0.30	0.18	0.24	0.52
155	P1LGRG D	Laundry and garment repair	3.6	0.1	-0.03	0.07	0.12	0.57
156	P1BEAG D	Beauty shops, including combination	3.9	0.5	0.08	-0.09	0.17	0.76
157	P1BARG D	Barber shops	2.8	0.0	0.01	0.08	0.11	0.56
158	P1WCRG D	Watch, clock, and jewelry repair	3.3	0.0	-0.01	-0.30	-0.03	0.66
159	P1CRPG D	Miscellaneous personal services	3.8	0.5	0.17	0.11	-0.02	0.62
160	P1BROG C	Brokerage charges and inv. couns.	1.2	1.0	0.30	0.50	0.01	5.18
161	P1BNKG C	Bnk srv. chges, trust serv., s-d box rental	5.7	1.2	1.81	-0.70	0.39	1.02
162	P1IMCG D	Commercial banks	2.4	1.0	-0.18	0.76	0.18	2.93
163	P1IMNG D	Other financial institutions	15.0	1.4	0.19	-0.32	0.58	3.05
164	P1LIFG C	Exp. of handl. life ins. and pension plans	2.3	1.2	-0.37	-0.24	0.49	0.45
165	P1GALG C	Legal services (65)	4.4	1.0	0.60	-0.41	0.14	0.91
166	P1FUNG C	Funeral and burial expenses	3.2	0.2	0.47	-0.61	0.35	0.57
167	P1UNSG D	Labor union expenses	4.1	0.2	-0.32	0.29	0.07	0.74
168	P1ASSG D	Profession association expenses	6.5	0.1	-0.23	0.03	-0.37	1.33
169	P1GENG D	Employment agency fees	5.5	0.0	1.40	-0.11	-0.04	1.03
170	P1AMOG D	Money orders	5.3	0.0	1.12	-0.24	-0.21	1.09
171	P1CLAG D	Classified ads	5.4	0.0	1.15	-0.23	-0.16	1.09
172	P1ACCG D	Tax return preparation services	5.2	0.1	0.97	-0.31	-0.11	1.12
173	P1THEG D	Personal business services, n.e.c.	7.1	0.1	0.61	-0.55	-0.03	1.66
174	P1PEDG D	Private higher education	4.4	0.7	-0.25	-0.13	0.02	0.89
175	P1GEDG D	Public higher education	4.1	0.7	0.52	-0.27	0.07	0.89
176	P1ESCG D	Elementary and secondary schools	4.3	0.4	-0.47	0.20	-0.02	0.84
177	P1NSCG D	Nursery schools	4.8	0.1	-0.63	0.01	0.02	1.05
178	P1VEDG D	Commercial and vocational schools	4.1	0.4	-0.96	-0.38	0.20	0.88
179	P1REDG D	Foundations and nonprofit research	4.5	0.2	-0.37	-0.27	-0.03	1.05
180	P1POLG D	Political organizations	8.2	0.0	0.04	0.39	-0.32	1.83
181	P1MUSG D	Museums and libraries	5.7	0.1	-0.70	0.08	-0.13	1.18
182	P1FOUG D	Foundations to religion and welfare	5.4	0.2	-0.54	0.09	0.01	1.11
183	P1WELG D	Social welfare	3.3	1.7	-0.39	0.12	-0.01	0.54
184	P1RELG D	Religion	5.0	0.7	0.17	0.19	-0.09	1.11
185	P1AFTG D	Passenger fares for foreign travel	9.8	0.5	-0.95	0.39	-0.08	2.32
186	P1USTG D	U.S. travel outside the U.S.	9.6	0.6	-2.04	0.50	0.15	2.16
187	P1FTUG D	Foreign travel in U.S.	3.6	1.0	-0.20	0.00	0.04	0.62

A.2 State-space representation of the dynamic factor model, the log-likelihood function, and the EM algorithm.

Let ρ be an *N*x*N* diagonal matrix with the ρ_i, let p be the order of the VAR, and let the $N\times 1$ vector $y_t = \pi_t - \rho\pi_{t-1} - \alpha$. Then, the unobserved-components model in (5)-(7) can be written in state-space form as:

$$y_t = Hs_t + e_t \tag{A.1}$$

$$s_t = Fs_{t-1} + G\varepsilon_t \tag{A.2}$$

where, $s_t = (x_t^{'}\ x_{t-1}^{'}\ \ldots\ x_{t-p+1}^{'})'$ with $x_t = (a_t\ \ R_t')'$ and:

$H = \begin{bmatrix} l & \Gamma & -\rho l & -\rho\Gamma & 0_{(N,(p-2)*(k+1))} \end{bmatrix}$, $\quad F = \begin{pmatrix} \Phi_1,\ldots,\Phi_{p-1} & \Phi_p \\ I_{(p-1)(k+1)} & 0_{(p-1)(k+1),k+1} \end{pmatrix}$, and

$C = \begin{pmatrix} I_{k+1} \\ 0_{(p-1)(k+1)} \end{pmatrix}$. The Gaussian log-likelihood for the unknown parameters conditional on $\{y_t\}_{t=2}^{T}$ can be computed using the Kalman filter innovations and their variances as described in Hamilton (1993, Chapter 13).

The EM algorithm is a well-known approach (Watson and Engle, 1983, Shumway and Stoffer, 1982) to maximize the Gaussian log-likelihood function for state-space problems. The method is convenient here because it straightforward to compute the expected value of the "complete data" ($\{y_t,\ s_t\}$) sufficient statistics conditional on the observed data ($\{y_t\}$), and because maximization of the complete data Gaussian likelihood follows from familiar regression formulae. The standard linear regression formulae are modified in two ways to estimate the parameters in (A.1)-(A.2). First, Gauss-Seidel/Cochrane-Orcutt iterations are used to estimate ρ conditional on α and Γ, and α and Γ conditional on ρ. Second, Γ is estimated subject to the constraint $l\,\Gamma = 0$ in (11) using the standard restricted least squares formula, in order to impose the normalization that we used.

While there are many parameters to estimate (971 in the benchmark model), there are two features of the model that make estimation feasible. First, while *N* is large, because *R* is diagonal, the sufficient statistics for the complete data likelihood can be computed in $O(Tm)$ calculations, where *m* is the dimension of the state vector *s*. Second, because N and T are large, the principal component estimators of $(a_t \;\; R_t')$ are reasonably accurate and regression based estimators of the model parameters can be constructed using these estimates of the factors. These principal component based estimates serve as useful initial values for the MLE algorithm. (See Doz, Giannone and Reichlin, 2006, for further discussion.) Results reported in the text are based on 40,000 EM iterations, although results using 5,000 iterations are essentially identical.

A.3 MLEs for the benchmark model

Table A1 includes the estimates of Γ, ρ, and σ_e for the benchmark 3-factor model. The estimated parameters in the VAR(4) state transition equation are

$$\Phi_1 = \begin{bmatrix} 0.40 & -0.10 & 0.35 \\ 0.44 & 0.63 & -0.01 \\ -0.72 & -0.25 & 1.33 \end{bmatrix},\ \Phi_2 = \begin{bmatrix} 0.73 & 0.06 & -0.28 \\ -0.19 & 0.06 & 0.06 \\ 1.14 & 0.21 & -0.71 \end{bmatrix},\ \Phi_2 = \begin{bmatrix} 0.00 & -0.13 & -0.05 \\ -0.45 & 0.16 & -0.10 \\ -0.30 & -0.36 & 0.36 \end{bmatrix}$$

$$\Phi_4 = \begin{bmatrix} -0.13 & 0.17 & -0.01 \\ 0.20 & 0.15 & 0.12 \\ -0.11 & 0.39 & -0.11 \end{bmatrix},\ Var(\varepsilon) = \begin{bmatrix} 0.40 & -0.16 & 0.45 \\ -0.16 & 1.0 & 0 \\ 0.45 & 0 & 1.0 \end{bmatrix}$$

A.4 Estimating υ_t

Recall that $\upsilon_t = a_t - E(a_t \mid \{R_\tau\}_{\tau=1}^{T})$. The projection $E(a_t \mid \{R_\tau\}_{\tau=1}^{T})$ is computed from the Kalman smoother from a state space system with state equation given by (A.2) and observation equation given by $f_t = [0 \;\; I_k \;\; 0_{(k,\ (k+1)p)}]s_t$. Finally, letting $q_{t/T} = \hat{E}(q_t \mid \{\pi_{i\tau}\}_{i=1,\tau=1}^{N,T})$ for any variable q_t, the law of iterated expectations implies that $v_{t/T}$ can be computed from the formula $v_t = a_t - \hat{E}(a_t \mid \{R_\tau\}_{\tau=1}^{T})$ by replacing a_t by $a_{t/T}$ and R_τ by $R_{\tau/T}$.

Table 1. Fraction of Variability of Inflation associated with Pure Inflation

Average Squared Coherence over frequencies (SEs in parentheses)

Inflation measure	Frequencies	
	All	$\pi/32 \leq \omega \leq \pi/6$
Usual Measures		
Headline PCE	0.16 (0.04)	0.15 (0.07)
Headline GDP	0.20 (0.04)	0.15 (0.07)
Headline CPI	0.12 (0.03)	0.15 (0.06)
Available Pure Measures		
Core PCE	0.24 (0.05)	0.21 (0.09)
Median CPI	0.14 (0.04)	0.18 (0.08)
187 Sectoral Inflation Rates		
25^{th} Pecentile	0.03	0.02
Median	0.05	0.05
75^{th} Percentile	0.07	0.08

Notes: PCE is the Personal Consumption Expenditures deflator, GDP is the Gross Domestic Product deflator, and CPI is the Consumer Price Index. Median CPI inflation is from the Federal Reserve Bank of Cleveland and these data are are available for $t \geq$ 1967:2. For the last panel, we computed the fraction of variability explained by pure inflation for each of the 187 goods' series, and report the 25%, 50%, and 75% values.

Table 2. Fraction of Variability of Real Variables associated with PCE inflation
Average Squared Coherence over frequencies (SEs in parenthesis)

Real Variable	Frequencies	
	All	$\pi/32 \leq \omega \leq \pi/6$
	a. No Controls	
GDP	0.11 (0.05)	0.28 (0.12)
Industrial Production	0.13 (0.06)	0.27 (0.14)
Consumption	0.15 (0.06)	0.28 (0.13)
Employment	0.19 (0.06)	0.32 (0.12)
Unemployment Rate	0.22 (0.07)	0.34 (0.15)
	b. Controls: Interest Rates, Stock Returns, Wages	
GDP	0.09 (0.05)	0.14 (0.07)
Industrial Production	0.13 (0.05)	0.12 (0.05)
Consumption	0.07 (0.04)	0.12 (0.06)
Employment	0.15 (0.04)	0.24 (0.09)
Unemployment Rate	0.14 (0.04)	0.18 (0.07)
	c. Controls: Interest Rates, Stock Returns, Wages, Exchange Rates ($t \geq 1973$)	
GDP	0.14 (0.05)	0.17 (0.08)
Industrial Production	0.15 (0.05)	0.14 (0.06)
Consumption	0.10 (0.05)	0.18 (0.08)
Employment	0.12 (0.04)	0.24 (0.10)
Unemployment Rate	0.13 (0.04)	0.20 (0.08)
	d. Controls: Relative-Price Factors	
GDP	0.02 (0.02)	0.01 (0.02)
Industrial Production	0.03 (0.02)	0.01 (0.02)
Consumption	0.06 (0.03)	0.03 (0.02)
Employment	0.08 (0.03)	0.03 (0.03)
Unemployment Rate	0.08 (0.03)	0.03 (0.03)

Notes: The results in panel (c) use only data only from 1973 onwards because of data availability for the weighted U.S. real exchange rate series.

Table 3. Fraction of Variability of Real Variables associated with Pure Inflation
Average Squared Coherence over frequencies (SEs in parenthesis)

Real Variable	Frequencies All	Frequencies $\pi/32 \leq \omega \leq \pi/6$
	a. No Controls	
GDP	0.05 (0.02)	0.09 (0.05)
Industrial Production	0.06 (0.02)	0.09 (0.06)
Consumption	0.08 (0.03)	0.08 (0.04)
Employment	0.07 (0.02)	0.12 (0.06)
Unemployment Rate	0.12 (0.03)	0.13 (0.07)
	b. Controls: Interest Rates, Stock Returns, Wages	
GDP	0.04 (0.02)	0.05 (0.03)
Industrial Production	0.05 (0.02)	0.04 (0.02)
Consumption	0.05 (0.02)	0.06 (0.03)
Employment	0.06 (0.02)	0.10 (0.04)
Unemployment Rate	0.12 (0.03)	0.07 (0.03)
	c. Controls: Interest Rates, Stock Returns, Wages, Exchange Rates ($t \geq 1973$)	
GDP	0.03 (0.02)	0.07 (0.04)
Industrial Production	0.04 (0.02)	0.04 (0.03)
Consumption	0.04 (0.02)	0.06 (0.04)
Employment	0.06 (0.02)	0.15 (0.07)
Unemployment Rate	0.10 (0.02)	0.09 (0.05)

Notes: The results in panel (c) use only data only from 1973 onwards because of data availability for the weighted U.S. real exchange rate series.

Table 4. Monetary Policy and PCE Inflation
Average Squared Coherence over frequencies (SEs in parenthesis)

Monetary variable	Frequencies	
	All	$\pi/32 \le \omega \le \pi/6$
Money growth		
M0	0.05 (0.03)	0.03 (0.04)
M1	0.02 (0.02)	0.02 (0.03)
M2	0.10 (0.04)	0.16 (0.10)
Nominal Interest Rate		
Federal Funds Rate	0.14 (0.05)	0.41 (0.14)
3-Month T-bill Rate	0.12 (0.05)	0.33 (0.15)

Table 5. Monetary Policy and Pure Inflation
Average Squared Coherence over frequencies (SEs in parenthesis)

Monetary variable	Frequencies	
	All	$\pi/32 \le \omega \le \pi/6$
Money growth		
M0	0.04 (0.02)	0.01 (0.02)
M1	0.06 (0.03)	0.01 (0.02)
M2	0.03 (0.02)	0.01 (0.02)
Nominal Interest Rate		
Federal Funds Rate	0.11 (0.04)	0.27 (0.10)
3-Month T-bill Rate	0.12 (0.03)	0.27 (0.12)

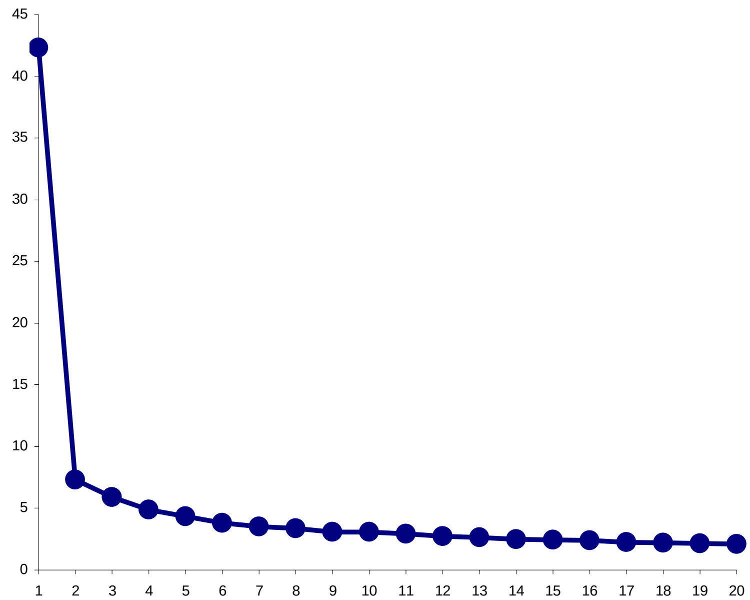
Table 6. Robustness of Results to Model Specification
Average Squared Coherence over business cycle frequencies (SEs in parenthesis)

Factor Estimates	VAR	$\hat{\upsilon}_t^{Benchmark}$	Core PCE Inflation	Real GDP	Money (M2)	Interest Rate (FFR)
			Benchmark Model			
(1,1,0)	D,4	1.00	0.21 (.09)	0.05 (0.03)	0.01 (0.02)	0.27 (0.10)
			Using Alternative Parametric Factor Estimates			
(1,1,0)	D,6	1.00	0.15 (0.06)	0.06 (0.03)	0.06 (0.07)	0.20 (0.09)
(0,0,0)	D,4	1.00	0.22 (0.09)	0.05 (0.03)	0.01 (0.02)	0.30 (0.11)
(0,0,0)	D,6	0.99	0.15 (0.06)	0.06 (0.03)	0.05 (0.07)	0.20 (0.09)
(1,1,0,0)	D,4	0.95	0.21 (0.09)	0.05 (0.03)	0.01 (0.01)	0.21 (0.10)
(1,1,0,0)	D,6	0.91	0.15 (0.06)	0.07 (0.04)	0.05 (0.06)	0.15 (0.09)
(1,1,0)	L,4	1.00	0.18 (0.07)	0.09 (0.04)	0.02 (0.03)	0.20 (0.11)
(1,1,0)	L,6	1.00	0.15 (0.07)	0.11 (0.04)	0.03 (0.05)	0.20 (0.11)
(0,0,0)	L,4	0.99	0.16 (0.06)	0.09 (0.04)	0.02 (0.03)	0.19 (0.11)
(0,0,0)	L,6	1.00	0.14 (0.06)	0.10 (0.04)	0.03 (0.05)	0.19 (0.11)
(1,1,0,0)	L,4	0.90	0.19 (0.07)	0.08 (0.04)	0.02 (0.03)	0.24 (0.10)
(1,1,0,0)	L,6	0.86	0.15 (0.07)	0.11 (0.04)	0.03 (0.04)	0.22 (0.10)
			Using Principal Component Factor Estimates			
PC-3	D,4	0.46	0.35 (0.13)	0.02 (0.02)	0.00 (0.01)	0.30 (0.12)
PC-3	D,6	0.49	0.25 (0.09)	0.02 (0.01)	0.06 (0.06)	0.28 (0.10)
PC-4	D,4	0.54	0.33 (0.12)	0.02 (0.02)	0.01 (0.02)	0.36 (0.10)
PC-4	D,6	0.56	0.22 (0.08)	0.03 (0.02)	0.08 (0.06)	0.33 (0.09)
PC-2	D,4	0.43	0.49 (0.15)	0.01 (0.01)	0.00 (0.01)	0.30 (0.13)
PC-2	D,6	0.40	0.30 (0.10)	0.03 (0.02)	0.06 (0.06)	0.29 (0.10)
PC-3	L,4	0.61	0.18 (0.07)	0.09 (0.04)	0.01 (0.01)	0.15 (0.09)
PC-3	L,6	0.54	0.16 (0.07)	0.04 (0.02)	0.05 (0.07)	0.16 (0.09)
PC-4	L,4	0.66	0.17 (0.06)	0.04 (0.02)	0.00 (0.01)	0.26 (0.10)
PC-4	L,6	0.65	0.13 (0.06)	0.05 (0.03)	0.07 (0.07)	0.24 (0.10)
PC-2	L,4	0.43	0.29 (0.10)	0.02 (0.02)	0.02 (0.04)	0.18 (0.10)
PC-2	L,6	0.38	0.21 (0.08)	0.05 (0.04)	0.04 (0.06)	0.21 (0.11)

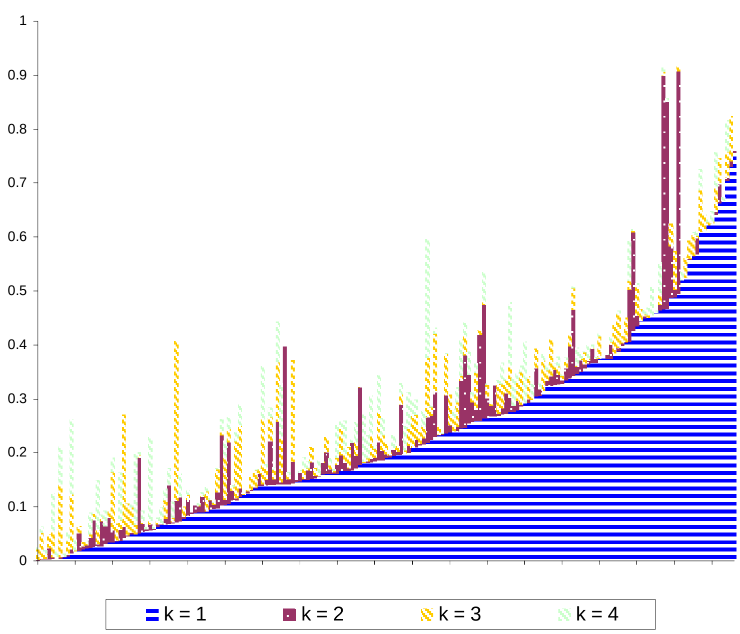
Notes: The first column describes the factor estimates, where the parametric estimates are based on signal extraction applied to (5)-(7) with parameters estimated by Gaussian MLE, and the numbers in parenthesis indicate the number of factors and whether the relevant factor is modeled as an I(1) or I(0) process. For example, "(1,1,0)" is a three factor model modeled as I(1), I(1), and I(0) processes. PC-*k* denotes a *k*-factor model estimated by principal components. The column labeled VAR shows the specification of the VAR used to compute the VAR-spectral estimates, where "D" and "L" denote first differences and levels specifications and the numbers 4 and 6 denote the number of lags in the VAR.

Figure 1. Choosing the number of factors

Panel a) Eigenvalues of the correlation matrix



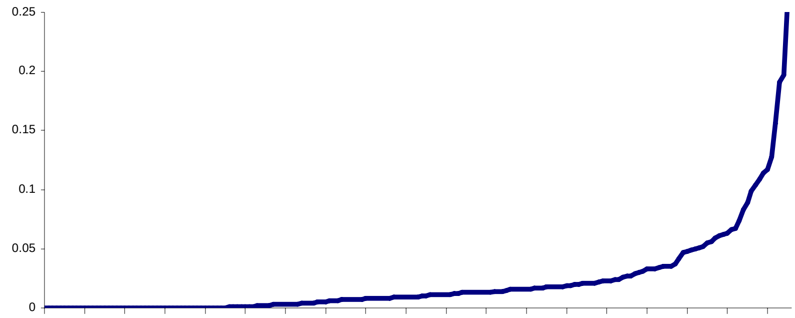
Panel b) Contribution of more factors to the R^2 of each good



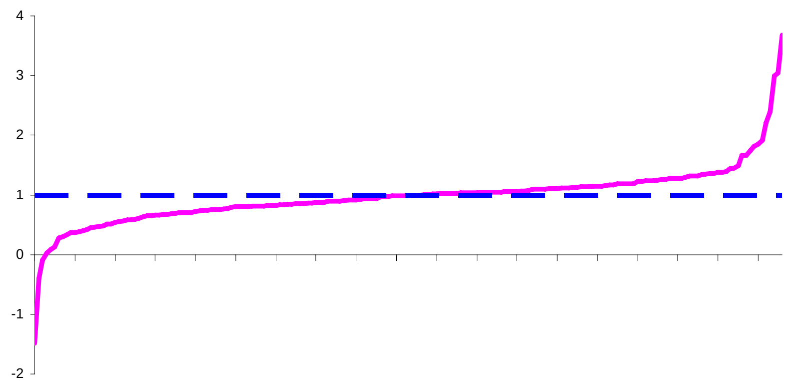
Notes: Panel a) shows the eigenvalues of the N×N sample correlation matrix of inflation rates. Panel b) shows the fraction of sample variance of inflation explained by k factors, where k varies from k=1 to k=4

Figure 2. Comparison with unrestricted factor model

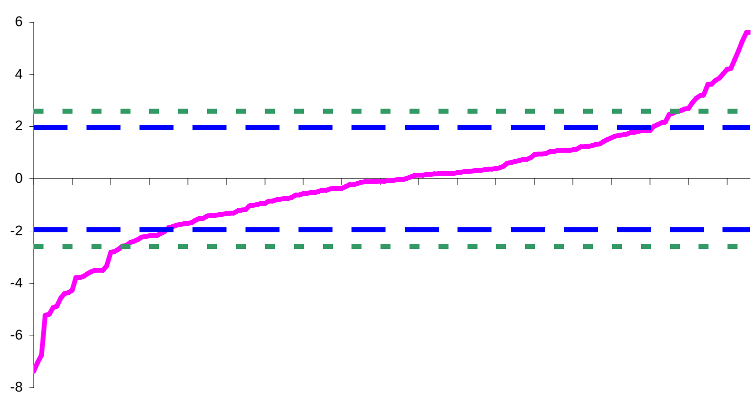
Panel a) Increase in R^2 from moving to unrestricted model



Panel b) Estimates of θ_i, the coefficient on absolute-price component



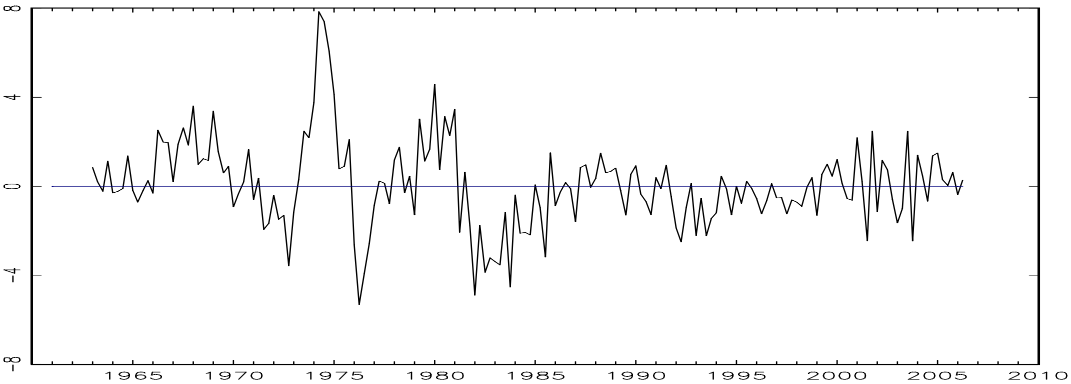
Panel c) Individual t-statistics for hypothesis θ_i=1



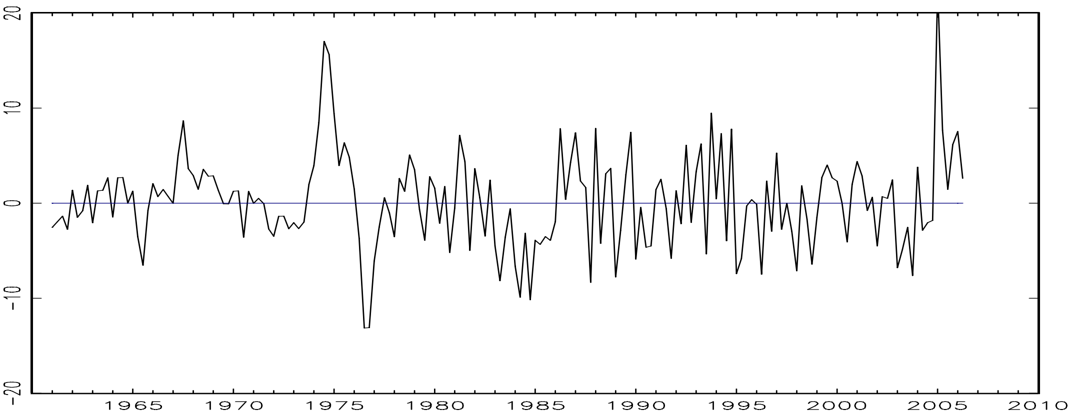
Notes: The horizontal axis in each panel goes from i = 1 to i = 187. In each panel, the goods are organized in increasing order.

Figure 3. Estimates of inflation and pure inflation

Panel a) Core PCE Inflation ($\pi_t - \pi_{t-8}$)



Panel b) Major Household Appliances Inflation ($\pi_{it} - \pi_{it-8}$)



Panel c) Pure Inflation ($\upsilon_t - \upsilon_{t-8}$)

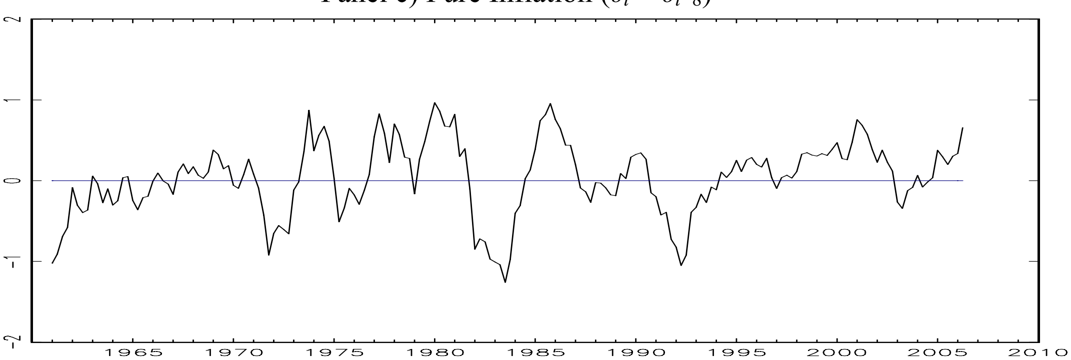


Figure 4. Alternative estimates of pure inflation ($v_t - v_{t-8}$):

Benchmark parametric model (solid blue) and principal components (dashed red)