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Ferre De Graeve and Karl Walentin

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E-mail: info@riksbank.se

Refining Stylized Facts from Factor Models of Inflation*

Ferre De Graeve† and Karl Walentin‡

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Abstract

Factor models of disaggregate inflation indices suggest that sectoral shocks generate the bulk of sectoral inflation variance, but no persistence. Aggregate shocks, by contrast, are the root of sectoral inflation persistence, but have negligible relative variance. We show that simple factor models do not cope well with essential features of price data. In particular, sectoral inflation series are subject to features such as measurement error, sales and item substitutions. In factor models, these blow up the variance of sector-specific shocks, while reducing their persistence. We control for such effects by estimating a refined factor model and find that inflation variance is driven by both aggregate and sectoral shocks. Sectoral shocks, too, generate substantial inflation persistence. Both findings contrast with earlier evidence from factor models, but align well with recent micro evidence. Our results have implications for the foundations of price stickiness, and provide quantitative inputs for calibrating models with sectoral heterogeneity.

Keywords: Inflation persistence, sticky prices, factor model, sectoral inflation
JEL Codes: E31,E32

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†Sveriges Riksbank, Research division. E-mail: ferre.de.graeve@riksbank.se.
‡Sveriges Riksbank, Research division. E-mail: karl.walentin@riksbank.se.

1 Introduction

The extent and nature of price rigidities are important inputs for many macroeconomic considerations. A recent body of research aims to shed light on this issue by identifying the sources of volatility and persistence in disaggregate (sectoral) inflation rates (Boivin, Giannoni and Mihov 2009; Maćkowiak, Moench and Wiederholt, 2009; Kaufmann and Lein, 2013). Based on a variety of estimated dynamic factor models for a number of different sectoral price data sets, two stylized facts emerge: *(i)* Sectoral inflation *volatility* is mostly due to sector-specific disturbances, while aggregate shocks explain only a small fraction of movements in inflation. *(ii)* Sectoral inflation *persistence* is driven by aggregate shocks. The response to idiosyncratic or sector-specific shocks, by contrast, is close to instantaneous.

The empirical findings on the sources of inflation persistence and volatility are used to validate foundations of price stickiness. For instance, Maćkowiak and Wiederholt (2009, 2010) and Maćkowiak et al. (2009) argue for rational inattention as the root of price stickiness because it can replicate swift responses to sector-specific shocks and sluggish adjustment to aggregate shocks. Carvalho and Lee (2011), Shamloo and Silverman (2010) show how models with time-dependent nominal rigidities can generate similar impulse responses.

We show that essential features of price data imply that the simple factor model used in the literature is potentially misspecified. Importantly, this misspecification has the tendency to push variance and persistence estimates of sector-specific shocks in the direction of the stylized facts. We propose and estimate a refinement of the simple factor model that resolves the misspecification and use it to re-assess the stylized facts.

It is well-known that factor models perform well in capturing aggregate dynamics. Studies that underline the favorable properties of factor models for the study of aggregate dynamics are Stock and Watson (1998), Forni, Hallin, Lippi and Reichlin (2000) and Onatski and Ruge-Marcia (2013).

Applied factor models, however, tend to treat aggregate and sector-specific sources of variance highly asymmetrically. On the one hand, aggregate dynamics are given ample flexibility; e.g. they can be driven by multiple factors, with different dynamic properties. On the other hand, sectoral dynamics are typically assumed to follow a scalar autoregressive process. The latter is an innocuous assumption for most of macroeconomics, in which the focus lies entirely on studying aggregate dynamics (e.g. Reis and Watson, 2010; Baumeister, Liu and Mumtaz, 2013).

The scalar process assumption for the sector-specific component is, however, instrumental to the *relative* properties of aggregate and sectoral shocks. It implies lumping all non-aggregate sources of volatility together into one (residual) sector-specific process. As a result, the variance and persistence of that process are not necessarily meaningful objects to validate theories against.

Due to two essential properties of price data, simple factor models of inflation indices can produce misleading statements about the relative importance and persistence of sector-specific vs. aggregate shocks.

A first property is the presence of measurement error. Inflation indices are based on samples drawn from actual prices of various goods collected by agents across various stores around the country. This implies that at least two types of measurement error affect price collection. The first is due to the fact that agents cannot collect all prices from all stores/cities/products. Selecting which prices to sample introduces sampling variance. Shoemaker (2007) estimates that the sampling variance of collected prices is substantially larger than the variance of actual price changes for the median product in the data underlying the CPI. Beyond sampling variance, Eichenbaum et al. (2012) discuss numerous types of measurement error that affect price data collection. They argue that such measurement errors have led economists to believe prices move more than they actually do, with the majority of measured small price changes not reflecting actual changes in price.

A second property which may cause simple factor models of inflation to fare poorly is the presence of sales and product substitutions. A vast body of research on micro price data has shown that accounting for irregular price changes such as sales has a dramatic impact on measures of price rigidity (e.g. Nakamura and Steinsson, 2008; Kehoe and Midrigan, 2012; Eichenbaum, Jaimovich and Rebelo, 2011). For instance, Nakamura and Steinsson (2008) have shown that filtering out sales increases the median measured duration of prices to 7-9 months, from an initial estimate of 4.3 in Bils and Klenow (2004). Similarly, product substitutions can impart changes in measured prices that may not reflect actual changes in prices. Substitutions too, can have substantial effects on measures of inflation persistence (e.g. Bils and Klenow, 2004; Nakamura and Steinsson, 2012). In view of these properties, the bulk of subsequent research on micro prices has aimed to control for the presence of sales and substitutions when evaluating the properties of (regular) price changes.

Simple factor models are not well suited to handle these essential features of price data. Basically, each of these properties generates additional sector-specific inflation variance with low persistence. A simple factor model will lump such irregular price fluctuations together with (possibly persistent) sector-specific structural shocks. As a result, measurement error, sales and substitutions have the scope to drive the simple factor model exactly in the direction of the stylized facts *(i)* and *(ii)*, by increasing the measured variance of sectoral shocks, while lowering their persistence.

We estimate a generalization of the simple factor model. The model nests the simple factor model of Boivin et al. (2009) and additionally allows for the presence of measurement error, sales and substitutions. The simple factor model is overwhelmingly rejected in favor of the refined model. Specifically, 88% of the sectors in the US personal consumption expenditure (PCE) data used by Boivin et al. (2009) have inflation dynamics that are better described by a process that allows for multiple sector-specific components.

The rejection of the simple factor model can be due to a variety of underlying reasons. These include measurement error, sales and substitutions, but also multiple shocks affecting sectors and/or firms. Disentangling the exact source is a daunting task and definitive conclusions to that end require product-level data. Yet, irrespective of its source, the multicomponent nature of sector-specific shocks has implications for stylized facts *(i)* and *(ii)*.

First, one of the identified sectoral components exhibits substantial persistence. Particularly, the generalized model implies a cross-sectional distribution of persistence with a median of 0.4 and a mode above 0.8. By contrast, the cross-sectional distribution of persistence estimates in the simple factor model of Boivin et al. (2009) is relatively flat and symmetric around a zero median. Thus, stylized fact *(ii)* is a result of measuring persistence of a composite process, masking underlying persistence.

Second, regarding the relative volatilities of sectoral and aggregate shocks in stylized fact *(i)*, the implication of the rejection of the simple factor model depends on the source of the multiple components. At a minimum, stylized fact *(i)* requires a different interpretation. In particular, if the multicomponent nature is due to the presence of multiple structural shocks then the standard formulation of the rational inattention model (à la Maćkowiak and Wiederholt) does not obviously explain it. Similarly, basic versions of models with time-dependent price setting (à la Calvo) also have a hard time matching the fact that within a sector some changes in prices are persistent while others are not. There are current efforts to understand how these types of frictions work in richer environments.[1] If it is the presence of multiple structural shocks that causes the rejection of the simple factor model, then our estimates suggest that model development should aim not just at generating persistence in response to sector-specific shocks. In addition, it should also aim at providing reasons for why it coexists with non-persistent fluctuations within the same sector.

There is, however, another possible interpretation. Existing micro-evidence as well as validation exercises with our model support the case that at least part of the source of the additional components is due to measurement error, sales and substitutions. Put differently, the high-frequency components may well be the result of non-structural measurement issues. In this case, a simple factor model will misleadingly interpret all sector-specific fluctuations as structural and thus overestimate variance and underestimate persistence. Under this plausible alternative, it turns out that while on average sectoral

[1] For instance, Pastén (2012) describes how rational attention allocation in multi-product firms may lead to less persistence in response to aggregate shocks and more persistence following sectoral shocks. Carvalho and Lee (2011) discuss the importance of complementarities in economies with input-output interactions.

shocks are still more important than aggregate shocks, this is far from general. In particular, for one quarter of all sectors volatility is predominantly driven by aggregate shocks. This stands in contrast to stylized fact *(i)*, which has led the field to disregard models that attribute a significant role to aggregate shocks.

Thus, the rejection of the simple factor model implies a change in facts that has a major impact on identifying the sources of nominal rigidities. The current litmus test for sectoral models of price setting is whether they can replicate stylized facts *(i)* and *(ii)*. Our results suggest that this test has prematurely refuted models that cannot deliver immediate responses to sector-specific shocks and provided support for other models that could. Similarly, the test has implied disregarding models in which aggregate shocks play a larger role than sector-specific shocks in terms of variance. Our results indicate that this is in fact a true feature of many – though not all – sectors. Therefore, stylized facts *(i)* and *(ii)* should not be used as a basis to repudiate theories of price rigidities.

The paper is organized as follows. We start by reproducing the stylized facts using a simple factor model. Then, in Section 3, we show what can go wrong with factor models for inflation indices. Section 4 lays out essential features of price data as documented in the recent literature. Subsequently, in Section 5, we propose a refinement of the simple factor model and estimate it for US PCE data. In Section 6 we discuss the implications of our results for the stylized facts. After assessing the robustness of our results in Section 7, we conclude.

2 A simple factor model for sectoral inflation

Consider the following decomposition of sectoral inflation π_{it} into a common and a sector-specific component

$$\begin{aligned} \pi_{it} &= COM_{it} + SEC_{it} & (1) \\ &= \lambda_i' C_t + e_{it}. & (2) \end{aligned}$$

Here, $COM_{it} = \lambda_i' C_t$, and C_t is a $N \times 1$ vector of common factors. These factors are distilled from a large cross-section of macroeconomic and/or sectoral time series, X_t. The factor loadings λ_i measure the dependence of inflation in sector i on aggregate, or common, conditions. The remainder, e_{it}, is a purely sector-specific scalar process. The dynamics of sectoral inflation originate from both the common component and the sectoral component, through

$$\begin{aligned} C_t &= \Phi(L) C_{t-1} + v_t, & (3) \\ e_{it} &= \rho_i(L) e_{it-1} + u_{it}. & (4) \end{aligned}$$

With this kind of decomposition at hand, Boivin et al. (2009) and Maćkowiak et al. (2009) decompose the variance, $\sigma^2(\pi_{it})$, and persistence, $\rho(\pi_{it})$, of sectoral inflation into a common and a sector-specific part.[2]

As a quantitative reference for what follows, we use the data of Boivin et al. (2009) to estimate the model (1)-(4). The data for π_{it} are monthly PCE price indices for 190 sectors over the period 1976:1-2005:6. We extract 5 common factors C_t from a total of 653 monthly series. In particular, X_t consists of 111 macroeconomic indicators, 190 sectoral PCE and 154 Producer Price Index (PPI) inflation series as well as 190 sectoral PCE quantity series. In addition, X_t contains 4 PCE price aggregates and the corresponding quantity aggregates.[3] We set lag length to 13 for all lag polynomials, in analogy to Boivin et al. (2009), though results are very similar using standard lag selection criteria.

Figure 1 plots the breakdown of PCE inflation variance and persistence into a common and a sector-specific component across all sectors. Comparing the upper and lower left plots, it is clear that inflation variance is primarily induced by sector-specific shocks. The variance contribution of common shocks, by contrast, is concentrated toward zero. The right-hand plots of the figure show the decomposition of persistence across sectors. Sectoral shocks generally do not tend to cause much persistence. The distribution of persistence of the sectoral component is relatively flat, with the median sector having no persistence at all. The picture is dramatically different for the persistence of the aggregate component. Its distribution across sectors is strongly negatively skewed, with almost all sectors bunching up at very high levels of persistence.

These results are fully in line with those of Boivin et al. (2009) and Maćkowiak et al. (2009). In sum, from both the literature and our own simple factor model two seemingly robust conclusions emerge. For most sectors,

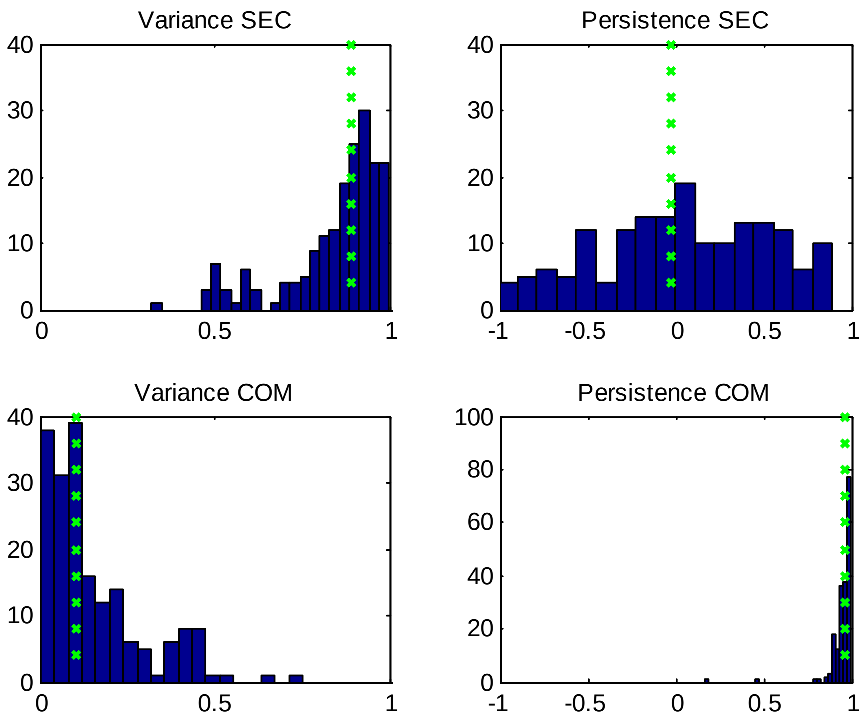
$$\begin{aligned} \text{Stylized fact 1} &: \quad \sigma^2(COM_{it}) < \sigma^2(SEC_{it}) \\ \text{Stylized fact 2} &: \quad \rho(COM_{it}) > \rho(SEC_{it}) \approx 0. \end{aligned}$$

In words, for almost all sectors, inflation volatility is predominantly driven by non-persistent sector-specific shocks, while inflation persistence is due to the common component.

[2] There are different ways to estimate such a decomposition. Boivin et al. (2009) take a two step approach in which one first retrieves the common factors by principal components analysis, and subsequently estimates the observation equation (2) and the transition equations (3) and (4). Maćkowiak et al. (2009) opt for a Bayesian state-space model in which this is done jointly.

[3] We closely follow Boivin et al. (2009), with two minor exceptions. First, we do not force the Fed Funds rate to be a separate factor. Second, we estimate the observation equation by maximum likelihood, which is useful for later reference. Neither difference is quantitatively important for what follows.

Figure 1: Benchmark model - variance and persistence



Note: Inflation is standardized, such that $\sigma^2(\pi_{it}) = 1, \forall i$. Following Boivin et al. (2009), persistence is measured as the sum of the polynomial coefficients estimated for COM_{it}, and SEC_{it}. There is no natural lower bound on this persistence measure. To maintain visibility in the figures, we limit the scale to [-1,1]. The medians – green x's – and histograms take into account all sectors.

3 Factor models and measurement error

Factor models perform well in the presence of measurement error or misspecification, as shown in, among others, Stock and Watson (1998). This statement is, however, subject to an important qualification. The excellent performance of factor models concerns the identification of the common factors (C_t) and their loadings (λ_i). It does not pertain to inference on the residual.

This qualification is not always addressed in applied work. At times, this may well be innocuous. In fields where residual properties matter for the interpretation of the results, it is not. The reason is that the mere presence of measurement error points to a clear form of misspecification in the simple factor model: e_{it} is not a scalar process, but has multiple components.

To convey why the dimensionality of e_{it} could matter for the study of inflation variance and persistence, consider the following example. Suppose inflation in sector i is driven by an aggregate component, COM_{it} as before, an AR(1) sector-specific shock P_{it}, with $\rho(P_{it}) > 0$, and an additional sector-specific component S_{it}. Let S_{it} have positive variance,

$\sigma^2(S_{it}) > 0$, and be orthogonal to P_{it}, $S_{it} \perp P_{it}$. Then

$$\begin{aligned}
\pi_{it} &= COM_{it} + SEC_{it} = \lambda_i' C_t + \underbrace{P_{it} + S_{it}}_{e_{it}} \\
\sigma^2(SEC_{it}) &= \sigma^2(e_{it}) = \sigma^2(P_{it}) + \sigma^2(S_{it}) \\
\rho(SEC_{it}) &= \rho(e_{it}) = \rho(P_{it} + S_{it}) = \frac{\sigma^2(P_{it})\rho(P_{it}) + \sigma^2(S_{it})\rho(S_{it})}{\sigma^2(P_{it}) + \sigma^2(S_{it})}.
\end{aligned}$$

It is immediate that

$$\sigma^2(SEC_{it}) > \sigma^2(P_{it})$$

and if $\rho(S_{it}) < \rho(P_{it})$, then

$$\rho(SEC_{it}) < \rho(P_{it}).$$

Interestingly, the biases resulting from the presence of S_{it} work exactly in the direction of the stylized facts: simple factor models have invariably found sector-specific shocks to be very volatile and non-persistent. The literature studying micro price data suggests there are good a priori reasons to expect additional components S_{it}, with $\rho(S_{it}) \leqslant 0$, to be important. We now discuss those reasons.

4 Prices and measurement

In this section we discuss measurement of goods prices. In particular, we document the scope for classical measurement error, sales and item substitutions. We also spell out the inflation dynamics they imply.

The scope for measurement error in the collection of prices is widely recognized. Shoemaker (2007) provides estimates of the errors associated with sampling. For the vast majority of the detailed expenditure categories in the CPI – corresponding to the PCE sectors we study – the median standard error is substantially larger than the median price change at the monthly frequency. The basic problem is that only a small number of prices, slightly above 200 price quotes per CPI entry level item, are sampled at this level of disaggregation and frequency.[4] In other words, at the level of disaggregation of the data we use, sampling error is a major concern.

Eichenbaum et al. (2012) point out several particular issues in price measurement that yield observed price changes even when the true price is unchanged. The largest issue, for this purpose, is the practice of measuring prices using unit value indices, i.e. as a ratio of sales revenue to quantity sold. This implies that a change in the composition of customers, and thereby in discounts, or any non-linearity in the contract will induce a change in the measured price. Another issue is uncorrected quality improvement. They document that these problems exist both in CPI data and most scanner data from retailers.

[4] More details are provided in Appendix C.

All but one of the above mentioned types of measurement error induce a classical uncorrelated term in the measured *price level*. The top left panel of Figure 2 illustrates the dynamics. The corresponding inflation dynamics is illustrated in the top right panel. This type of measurement error generates negative autocorrelation in inflation.

One can also argue for the existence of a classical measurement error in *inflation*, corresponding to permanent errors in the price level. In particular, any unrecorded change in quality, as noted by Eichenbaum et al. (2012), or size/quantity of a product will induce this type of error. The dynamics of this type of measurement error is illustrated in the bottom row of Figure 2.

The remainder of this section discusses two measurement issues that are particular for goods prices and have been widely emphasized in the micro price setting literature: sales and forced item substitutions (Golosov and Lucas, 2007; Klenow and Kryvtsov, 2008; Nakamura and Steinsson, 2008, 2009; Kehoe and Midrigan, 2012; Eichenbaum et al., 2011, Anderson, Nakamura, Simester and Steinsson, 2013).

Both sales and substitutions impart particular short-run dynamics on inflation. Sales are changes in a price that are undone after a brief period of time. They therefore generate negative autocorrelation in inflation. The simplest and most common sales definition used in the literature (e.g. by Nakamura and Steinsson, 2008) is the one-period symmetric 'V-shaped' pattern of the price level illustrated in the top row of Figure 2. The right-hand column of the same figure illustrates the corresponding inflation dynamics.

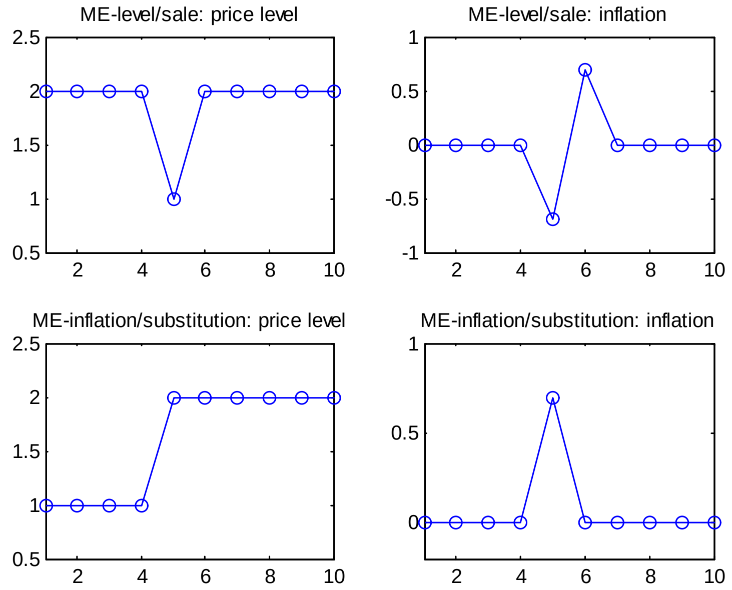
A forced item substitution occurs when the price surveyor can not record the price of the exact same good as the previous period at a given location. It implies a change in the measured price that does not necessarily reflect an actual decision to change price, but nevertheless generates a one-off blip in observed inflation. This is shown in the bottom row of Figure 2.

The product-level price literature has also established that the scope for sales and substitutions is huge. Cross-sectional heterogeneity aside, estimates for the monthly frequency of sales range from 7.4% (Nakamura and Steinsson, 2008) to over 20% (Klenow and Kryvtsov, 2008; Kehoe and Midrigan, 2012), and 3.4% (Bils and Klenow, 2004) to 5% (Nakamura and Steinsson, 2009) for item substitutions. The size of price changes induced by sales is also large – the median sale is 2.6 times the size of the median regular price change according to Nakamura and Steinsson (2008). The size of the error induced by each item substitution is unobserved, and is therefore harder to quantify.

5 Generalizing the simple factor model

As documented in the previous section, there is large scope for several measurement issues to affect measured disaggregated prices. These measurement issues imply particular inflation dynamics, as documented in the right-hand panel of Figure 2. In the product-

Figure 2: Dynamics induced by measurement error (ME), sales, substitutions



level pricing literature much work has been done to control for these issues, mainly regarding sales and substitutions. The importance of measurement error in prices is generally acknowledged in the literature. Bils and Klenow (2004) and Boivin et al. (2009) are but two examples where the effect of measurement error on measured persistence are discussed. But, the methods used in the literature studying sectoral inflation dynamics have not been well suited for – nor explicitly adjusted to – the presence of measurement error or other measurement issues.[5]

To control for the possible effects of measurement error, sales and substitutions we refine the simple factor model. We will refer to this refined model as the benchmark model. Essentially, the benchmark model aims to nest the simple factor model while allowing for the possible dynamics induced by measurement errors, sales and substitutions.[6]

5.1 Specification

In eq. (2), as before, sectoral inflation π_{it} loads on a number of common factors C_t that evolve according to eq. (3). At the idiosyncratic level ($SEC_{it} = e_{it}$), inflation is still driven by a persistent process, P_{it}, but now also contains two additional components.

[5] A separate issue is to what degree measurement error and other measurement issues are reduced by aggregating from the product level to the sectoral level. We address this issue quantitatively and in detail in Appendix C.

[6] Two related recent studies, Beck, Hubrich and Marcellino (2011) and Andrade and Zachariadis (2012) extend the simple factor model to allow for geographical differences, such as global, country or region specific factors. Here, the focus is on dynamics induced by essential features of price data.

The first additional component we allow for is an $iid-$component, I_{it}. Such a component can absorb measurement error in inflation or item substitutions, as in the bottom-right panel of Figure 2. The second additional component we introduce is a moving average component, M_{it}, that serves to absorb the pattern implied by sales or, alternatively, measurement error in the price level, as in the top-right panel of Figure 2.

Thus, the sector-specific component, previously eq. (4), now becomes

$$e_{it} = P_{it} + I_{it} + M_{it} \tag{5}$$

where

$$\begin{aligned} P_{it} &= \rho_i(L)P_{it-1} + \varepsilon_{it} && (6) \\ I_{it} &= \epsilon_{it} && (7) \\ M_{it} &= \xi_{it} - \xi_{it-1} && (8) \end{aligned}$$

and

$$(\varepsilon_{it}, \epsilon_{it}, \xi_{it})' \sim N(0_{3\times1}, D),\ D^{1/2} = \begin{bmatrix} \sigma_i^{\varepsilon} & 0 & 0 \\ 0 & \sigma_i^{\epsilon} & 0 \\ 0 & 0 & \sigma_i^{\xi} \end{bmatrix}.$$

The three (unobserved) components P_{it}, I_{it} and M_{it} have distinct persistence properties, and mutually orthogonal shocks ε_{it}, ϵ_{it} and ξ_{it}. We estimate the above factor model on the same data as Boivin et al. (2009). More precisely, we retain the factors from the simple model and estimate, for each sector, using maximum likelihood and the Kalman filter, the observation equation (2) accounting for (5)-(8).

While the distinct persistence properties in the above specification ensure theoretical identification, this does not reveal much about the empirical performance of the estimator in finite samples.[7] In Appendix A we document the favorable properties of the multi-component maximum likelihood procedure for various data-generating processes (DGP) of interest. In short, when the DGP has multiple components, the estimator identifies multiple components and recovers persistence estimates close to the DGP. Not surprisingly, for lower underlying persistence, the estimator has lower precision. Nevertheless, even when the DGP truly is a single component process, estimating a multicomponent process does not imply substantial biases. Importantly, on the other hand, estimating single component processes (ARs) on multicomponent data generates estimates not even in the ballpark of the true persistence.[8]

[7] Note that, theoretically, when $\rho_i(.)$ has zero coefficients at all lags, there is an identification issue, as the likelihood then is flat in σ_i^{ϵ} and σ_i^{ε}. In practice, this turns out not to play a role. In other words, these ridges are typically located away from the likelihood's maximum. We have also estimated Bayesian versions of the model. While these make it easier to achieve identification through the prior, they also tend to attribute non-zero prior variance to each component, which we prefer to not impose.

[8] Among other things, the appendix provides an example DGP with equal variances of the three

Two further remarks are in order. First, the above definition of M_{it} implies a quite restrictive definition for capturing sales. Nevertheless, this component will pick up a subset of sales and thereby alleviate the issues that follow from confounding several components into one scalar process. As discussed in Section 7, our results go through for alternative, less restrictive specifications of M_{it}. Second, in Appendix C we show that the dynamics of I_{it} and M_{it} are preserved when prices are aggregated from product-level to sector level.

5.2 Model selection

Observe that the benchmark factor model, through eq. (5), nests the simple factor model, via eq. (4). Therefore, standard model selection criteria are available to choose between the simple model and the benchmark factor model. If the additional components I_{it} and M_{it} are of no importance, the increase in the likelihood of the benchmark factor model relative to the simple model will be marginal. Selection criteria penalizing for the additional number of parameters (i.e. σ_i^{ϵ}, σ_i^{ξ}) will then favor the more parsimonious simple model.

Table 1 shows that in almost 90% of the sectors the data is better described by the benchmark factor model than by the simple model. In only 12% of all sectors there is no notable improvement in terms of fit by allowing multiple components at the sectoral level.

Table 1: Model selection criteria

	Simple	Benchmark
AIC	12%	88%
SBIC	12%	88%

Table 2 provides an alternative view on the estimated benchmark factor model. It characterizes sectors by the relevance of their sector-specific components.[9] A number of features stand out. First, all sectors have a persistent component. Second, for more than half of the sectors both I and M play a role. Third, only 11% of the sectors are well captured by a single component process.[10] Thus, from this perspective too, the scope for additional components is substantial.

Yet another way of evaluating the relevance of the additional components is by means of significance of point estimates. Table 3 shows how the number of significant shock-

components, a persistence of P_{it} of 0.5 and the resulting estimated AR persistence centered around 0 - very much like the estimates in the previous literature.

[9] For the purpose of this table, we consider a component irrelevant for a particular sector if it accounts for less than 1% of the variance in the sectoral component.

[10] Not surprisingly, these are also the sectors for which the information criteria select the simple model over the extended model.

Table 2: Sectors and idiosyncratic components

Components	% sectors
P	11%
I	0%
M	0%
$P+I$	24%
$P+M$	13%
$I+M$	0%
$P+I+M$	53%

variance estimates broadly confirms the scope for additional components in Table 2. Particularly, the fraction of sectors for which the variance of the I-component is significant is 69%, while the M-component's shock is significant in 61% of the sectors. Almost all sectors have $\sigma_\varepsilon > 0$.

Table 3: T-statistics: sector-specific shock variances

	t-stat>1.96 (% sectors)
$P : \sigma_\varepsilon$	94%
$I : \sigma_\epsilon$	69%
$M : \sigma_\xi$	61%

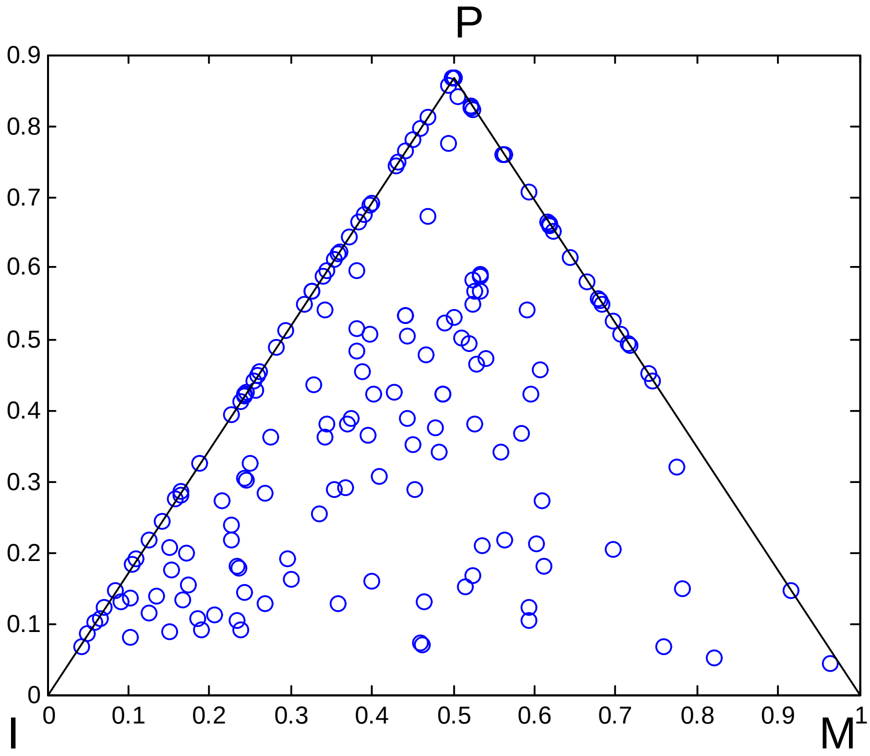
The additional components are also quantitatively important. Figure 3 decomposes the variance of the sectoral component into P, I and M for all sectors. A point at the origin implies that all the sectoral variance is attributed to the I component. A sector located at the top corner signifies 100% of its sector-specific variance stems from the P component, and analogously the right bottom corner signifies $\sigma^2(SEC_{it}) = \sigma^2(M_{it})$. If a sector is located on, say, the $I-P$ axis, this implies it has no M component. A key message from Figure 3 is the enormous degree of heterogeneity across sectors. Further details about the variance decomposition are also documented in Table 4. First, in half of the sectors, most of the variance in SEC is due to P. Conversely, the other half of the sectors have most of their sectoral variance coming from I and M. Second, I appears to be quantitatively more important than M at the sectoral level.

Table 4: Variance decomposition - SEC

	Median	Mean
P	0.51	0.52
I	0.29	0.32
M	0.11	0.16

Table 5 shows, for each component, the median and mean variance contribution to π_{it} across sectors. As expected, the variance contribution of the common component is

Figure 3: Variance contributions - SEC



around 10-15%, consistent with the evidence in the literature.[11] The remaining 85-90% inflation variance is driven by sector-specific shocks. As the next three rows in the table (and Figure 3) indicate, a non-negligible part of the sectoral variance is due to the I and M component. The median contribution of the persistent sectoral component P to total sectoral inflation is 43%.

Table 5: Variance decomposition - inflation

	Median	Mean
COM	0.10	0.17
SEC	0.89	0.85
P	0.43	0.44
I	0.25	0.27
M	0.09	0.14

[11] Because the benchmark model further develops the sector-specific component, one would expect the identification of the factors and the estimation of factor loadings to be largely unaffected (Stock and Watson, 1998). The biases we study should therefore have negligible impact on studies that solely focus on aggregate components, e.g. Reis and Watson (2010). In Appendix D we document the similarity in factor loadings between the simple and the benchmark factor models used here.

6 Re-evaluating the stylized facts

6.1 Persistence

Section 3 showed how multiple components could lead to underestimating persistence for the simple example of an AR(1) data generating process. For more elaborate processes (e.g. with longer lags) and persistence measures (e.g. sum of polynomial coefficients) the direction and size of the bias induced by sales and substitutions is less clear cut *a priori*. Whether persistence in the simple factor model is substantially biased is thus ultimately an empirical question.

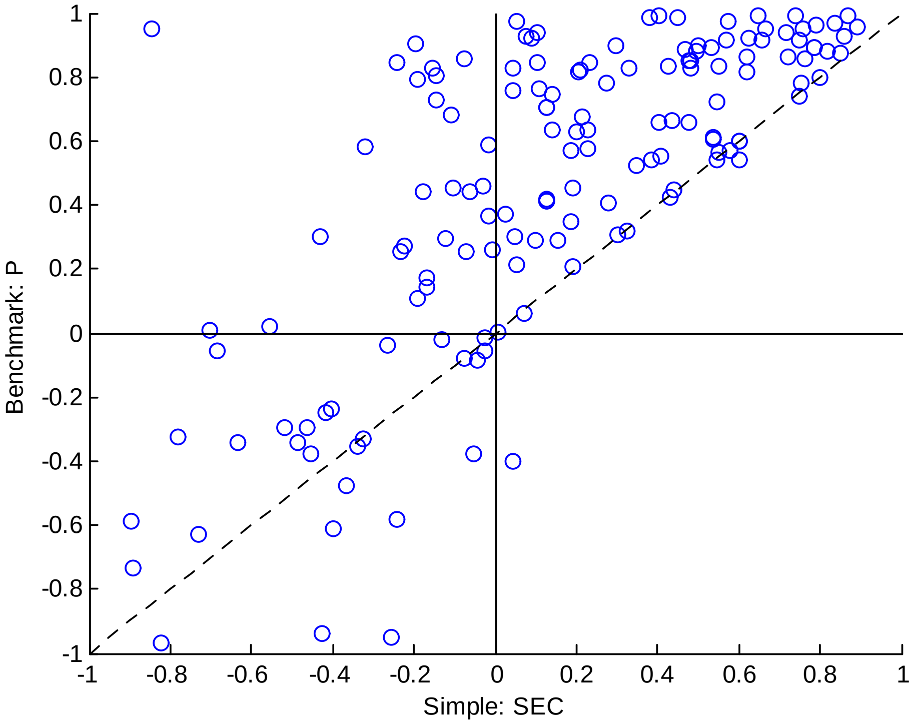
Figure 4 therefore compares persistence in the simple model (on the x-axis) to persistence in the benchmark factor model (y-axis). The result is overwhelmingly clear: 88% of all sectors lie above the 45°-line. In other words, the simple factor model substantially underestimates the persistence of sectoral shocks. The two right-hand quadrants contain sectors that exhibit positive persistence in the simple factor model (about 50% of all sectors). For these, the median persistence estimate is 47% higher in the benchmark model than in the simple model. In the upper left quadrant, the benchmark factor model finds positive persistence, where the simple model fails to detect any. This quadrant contains 15% of all sectors. For the remaining sectors, in the bottom left quadrant, neither of the factor models find any positive persistence.

These biases substantially alter the view on the persistence of sectoral shocks. The top row of Figure 5 first reprints the cross-section of persistence measures in the simple model. It is a rather flat distribution, with the median sector having zero persistence. This is the second stylized fact. The benchmark factor model (bottom row) shows that, actually, sectoral persistence is strongly negatively skewed. A lot of sectors cluster at very high levels of persistence. For the median sector, persistence is estimated at 0.4.

Thus, the rejection of the simple factor model has an immediate implication for stylized fact *(ii)*. It is not true that sectoral shocks do not generate persistence. Rather, sectoral inflation rates are also affected by high frequency sources of variance with no or negative autocorrelation. Simple factor models ignore that and lump these together with persistent shocks. Measuring persistence of the composite process will then bias measured persistence downward, thereby resulting in stylized fact *(ii)*.

From the evidence on persistence we conclude that there is no need to disregard models that fail to deliver stylized fact *(ii)*. The data suggest that sector-specific shocks do generate persistent inflation dynamics. But simple factor models fail to detect them because they confuse them with non-persistent sources of variance. We now turn to the interpretation of these additional components.

Figure 4: Persistence - Bias



6.2 Variance

There are two extremes in how to interpret the additional components. On the one hand, they may be structural shocks. If this is the case, contemporary models do not explain the multi-faceted nature of sector-specific dynamics. While stylized fact *(i)* still holds, models deemed to support it do not. On the other hand, the multiple components may be due to measurement issues. This second interpretation sees part of the sector-specific variance as non-structural and thus requires that it is abstracted from when evaluating structural models. Stylized fact *(i)* therefore should not guide validation of theories.

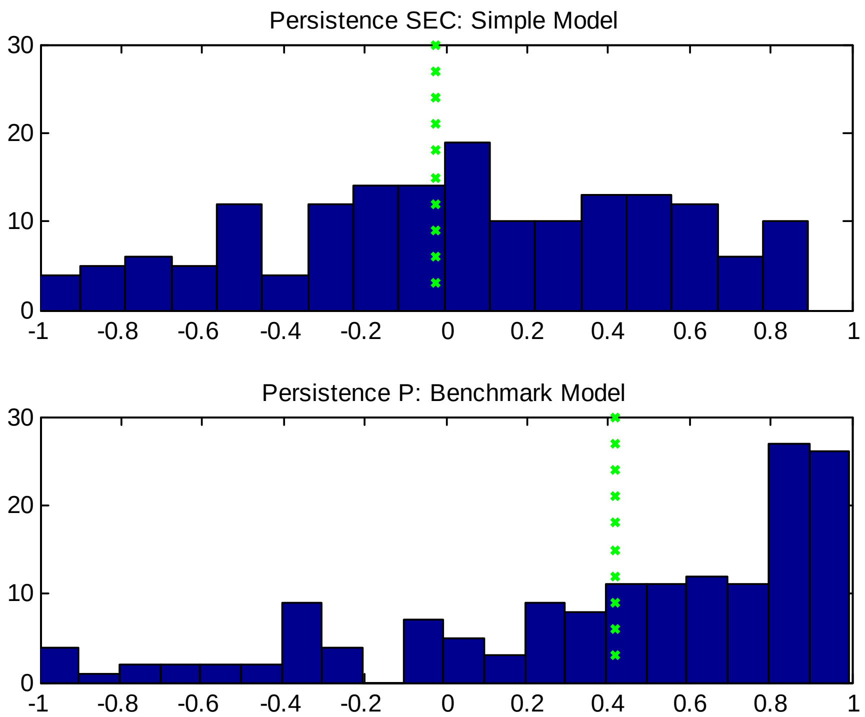
Section 4 provided evidence for the a priori plausibility of measurement error, sales and substitutions. In what follows, we perform a number of validation tests which support such an interpretation of the I and M components. But even if one does not abide this interpretation the mere presence of multiple components affects the type of economic environments factor models provide support for. We first discuss these implications.

6.2.1 Structural shocks

If one chooses to interpret I and M in a structural manner then it is not immediately obvious how some of the currently advocated models can explain them.

Consider first the Calvo model. Shamloo and Silverman (2010) and Carvalho and Lee

Figure 5: Persistence - Simple vs. benchmark factor model



(2011) show that the stylized facts *(i)* and *(ii)* can be explained with Calvo frictions once input-output linkages between sectors are incorporated in the model. Essentially, these allow sectors to behave differently conditional on aggregate shocks – where linkages matter – and on sector-specific shocks – where linkages matter only marginally. Interpreting the I and M component as structural implies that further conditionalities need to be addressed. Particularly, it begs an explanation for conditionality within a sector: why is it that a sector sometimes responds slowly (as implied by P), while at other times it does so immediately (due to I or M)? It is not obvious how a Calvo model would be able to generate such conditionality.

Second, contemporary models of rational inattention have argued that because sector-specific shocks are so volatile it pays off for agents to focus attention on them, implying a fast response to sector-specific shocks. Aggregate shocks, by contrast, receive less attention because they are much less volatile. Responses to them will therefore be sluggish. The multicomponent nature of sector-specific inflation dynamics challenges such an interpretation. From the perspective of an agent deciding on where to allocate her attention, incentives change. Particularly, inferring which of the sector-specific components fluctuates may place substantial additional required processing capacity on the agent. On the one hand, aggregate shocks may therefore become a more attractive alternative focal point. On the other hand, the relative properties of the various sector-specific components are inconsistent with the most basic implication of rational inattention: the most volatile component, P, is also the most persistent one for most of the sectors.

This does not necessarily mean that Calvo or rational inattention models are incapable of explaining these findings. However, in their current formulations they do not. Possible avenues to reconcile these theories with the multicomponent nature of sector-specific shocks include further heterogeneity in input-output structures, multi-product firms, and more.

6.2.2 Sales and substitutions

The prevalence of sales and substitutions in price data is one of the primary motivations for generalizing the simple factor model. We here validate this motivation by examining to what degree the presence of the I and M components in our benchmark factor model coincide with Nakamura and Steinsson's (2008, henceforth NS) product-level CPI data evidence. Our focus is on extremes: we compare whether a sector has a sales or substitution component at all in our results to the prevalence of sales and substitutions in that 'major group' according to NS.[12,13] As documented above in Table 2, sales and product substitution components, M and I respectively, are only present in a subset of the PCE sectors we study. In particular, Table 2 documents that 35% of sectors have no M component while 24% of sectors have no I component.

Table 6 documents the validation exercise of our M and I components vs. Nakamura and Steinsson's sales and substitutions. A name of a sector in bold typeface in the table indicates that the presence/absence of our M or I component coincides with NS sales and substitutions, while a sector name in normal typeface instead indicates conflicting results compared to NS. Italics denote inconclusive comparison.

NS document that Utilities, Vehicle fuel, Services (excl. travel) and Travel have virtually no sales, and at the opposite end of the spectrum that Apparel, Household Furnishing and Food (processed and unprocessed) have the highest prevalence of sales.

[12] The relationship between the variance of our sales (substitutions) component and the fraction of price changes that are sales (substitutions) is tenuous. Several factors, including heterogeneity across sectors in the relative size of sales price changes and in aggregation properties, distort the translation from micro price characteristics such as sales (resp. substitution) intensity to variance of M (resp. I). For an intuitive reason why aggregation need not preserve the relation between our components and the micro data, consider the following example. Two sectors A and B each have 100 products sampled. In sector A all products have sales, while in sector B only 1 product is ever on sale. Sales in sector B have no hope of averaging out across products, and will thus generate an M component in the index of sector B. The index for sector A, by contrast, may well not be affected much by product-level sales, as they have the scope to average out across products. Thus, despite being a sales-intensive sector, sector A may not require an M component. The opposite is true for sector B, despite having very few sales at the micro level. A similar logic applies to substitutions.

[13] An additional factor that complicates comparisons is the imperfect mapping between PCE sectors and the CPI 'major groups' and ELIs that NS reports.

Table 6: Overlap M and I components with micro sales and substitutions

	Highest	Lowest
Sales	**Clothes** **Hhs Furnishing** Food	**Electricity** **Gas** **Travel** *Services* Gasoline
Substitutions	**Clothes** **Transportation**	**Gasoline** **Electricity** **Water**

Note: List of sectors with highest (lowest) prevalence of sales or substitutions according to Nakamura and Steinsson (2008). Bold typeface indicates sectors where our result coincides with NS. Italics denote inconclusive comparison and normal typeface instead indicates conflicting results compared to NS.

Comparing our results for which sectors lack a M component we note that they coincide to a reasonable degree with NS sectors with least sales. Key utilities sectors (Electricity and Gas) have no M component. Gasoline, on the other hand, does have M component contrary do what NS sales results indicate.[14] In line with NS most travel sectors (Taxicab, Bus and Other) have no M component. Services (excl. travel) is a very diverse group. We note that a roughly average fraction (31%) of the PCE service sectors lacks an M component, while NS report above average sales in services.

Switching to sectors which have lots of sales according to NS, we confirm that sectors within Apparel (clothes for men, women and children, respectively) have a sales component. Four of the five Household Furnishing sectors have a sales component. For food sectors a non-negligible fraction, 25%, of them lack a sales component, contrary to the evidence in NS.

The analogous exercise for product substitution validates our method by lining up very well with NS. Their product-level data indicates that product substitution is most common in Apparel and Transportation goods (mainly cars), and least common in Vehicle fuel and Utilities. We find no substitution component in Gasoline or the utilities sectors Electricity and Water. Furthermore, and also in line with NS, we find a substitution component in all three clothes sectors and in all of the nine transportation good sectors.

To summarize, we find that our results on which sectors have sales and substitutions largely coincide with what NS find. This corroborates the a priori plausibility of the additional components M and I capturing sales and substitutions.

Since Bils and Klenow (2004) and Nakamura and Steinsson (2008), the micro price literature has almost invariably filtered out substitutions and sales in its study of regular price changes. The reason is obvious: since the models being validated tend not to feature

[14] The contradiction is with NS's benchmark results which are based on the BLS flag for sales. But, NS explain why the 'V-shaped' filter finds substantial amounts of sales for gasoline, also on product-level data. The issue is caused by high volatility in the price in combination with a tendency for discrete price changes.

sales or substitutions, the moments of the data models aim to match should not capture them either. Clearly, to the extent that I and M are indeed substitutions and sales, using the simple factor model for model validation does not follow this principle.[15]

If one does filter out I and M, stylized fact *(i)* changes substantially. Recall that simple factor models in the literature have the sharp result that for the median sector, sector-specific shocks are almost an order of magnitude more important than aggregate shocks. This large difference dominates any cross-sectional heterogeneity. Taking the ratio of common to sectoral variance contributions in the simple model, it appears that only 5 out of 190 sectors (3%) are more affected by aggregate shocks than by sectoral shocks. The first row of Figure 6 shows that result, with almost no mass below 1.

However, simple factor models ignore that much of the variance of the sectoral component is driven by sales and substitutions. Filtering those out, the benchmark model estimates sectoral shocks to be three to four times as volatile as aggregate shocks for the median sector, as is apparent in the second row of Figure 6. Importantly, aggregate shocks are more important than sector-specific shocks for one sector in four. Thus, while sectoral shocks tend to dominate, this is certainly not true for all sectors.

The fact that sales and substitutions have particular dynamics does not imply that they generally should be ignored. They may contain valuable information and should therefore be understood more fully. However, the (macro-)theory of sales is only just developing (Midrigan, 2011; Guimaraes and Sheedy, 2011; Kehoe and Midrigan, 2012; Matějka, 2011) and theory is largely non-existing for substitutions. Unless one validates models that incorporate sales and substitutions, the evidence models are required to match should filter out their effects. Stylized fact *(i)* should therefore not lead one to repudiate contemporary models.

6.2.3 Measurement error

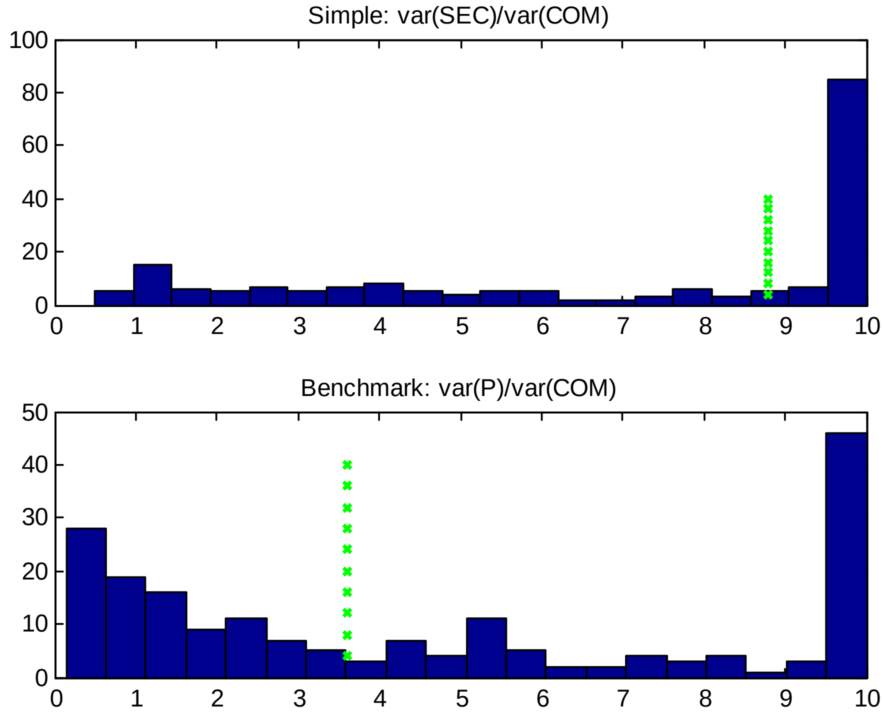
Measurement error in prices results in negative autocorrelation in inflation and can thus generate a M component. Analogously, measurement error in inflation will result in an *iid*-component, similar to I. As such, measurement error is observationally equivalent to sales and substitutions. It is known from the micro price data literature that various forms of measurement error are prevalent (Shoemaker, 2007; Eichenbaum et al., 2012).

The implication of measurement error for stylized fact *(i)* is straightforward: measurement error generates variance that should be ignored when evaluating structural models.

For some purposes it may actually be useful to quantify how much of the non-persistent sector-specific fluctuations is due to measurement error, rather than due to sales or substitutions. For instance, many studies make conjectures about plausible degrees of measurement error, in order to verify whether it could drive their results (e.g. Bils and Klenow,

[15] For an example that does abide this principle, see e.g. Bouakez, Cardia and Ruge-Mucia (2009). They compare a model without sales to statistics from micro data which filter out sales.

Figure 6: Variance ratios



Note: Due to the presence of sectors with virtually no variance in the common component, values above 10 are truncated at 10.

2004). To inform such questions, we here adapt our factor model to shed light on the importance of measurement error, relative to sales and substitutions.

One way to overcome the observational equivalence between sales and substitutions on the one hand, and measurement error in prices and inflation on the other, is to use quantities. A priori, there is no apparent reason to expect measurement error in prices to affect quantities. Sales and substitutions, by contrast, can be expected to influence quantities. In Appendix B, we lay out an extension to the factor model that separates measurement error from sales and substitutions. We here summarize the results of that model specification briefly, while the appendix contains the results on variance and persistence across sectors.

Table 7 indicates that for the median sector, 11% of inflation variance is due to measurement error (η). In the benchmark model (without quantities isolating measurement error), the I and M components seem to soak up that variance, as expected. Nevertheless, even in the model that accounts separately for pure measurement error, the I and M components still appear very relevant. Importantly, the conclusions for the relative variance and persistence of common and sectoral shocks remain unchanged from our benchmark model.

Table 7: Variance decomposition - measurement error

	Benchmark model		Accounting for measurement error	
	Median	Mean	Median	Mean
COM	0.10	0.17	0.11	0.16
SEC	0.89	0.85	0.89	0.85
P	0.43	0.44	0.47	0.46
I	0.25	0.27	0.18	0.23
M	0.09	0.14	0.07	0.15
η	–	–	0.11	0.16

6.3 Interpreting the stylized facts

The current litmus test for sectoral models of price setting is whether they can replicate stylized facts *(i)* and *(ii)*. However, the rejection of the simple factor model has stark implications for the stylized facts. Concerning stylized fact *(ii)*, failure to detect persistence to sector-specific shocks is a consequence of misspecification in the simple factor model. By controlling for dynamics consistent with measurement error, sales and substitutions, we eliminate a bias present in previous estimates and obtain a median persistence of the sectoral component around 0.4. The mode of the cross-sectional distribution of persistence is above 0.8. As a result, one should not disavow models that generate persistent responses to sector-specific shocks.

The rejection of the simple factor model has further implications for the litmus test applied in the literature, through stylized fact *(i)*.

On the one hand, if the additional components are structural, stylized fact *(i)* remains intact. However, by assuming that sector-specific shocks are all alike, it may have supported models it should not have. Instead, models should be required to generate, within sectors, both persistent and non-persistent responses to sector-specific shocks.

On the other hand, if the presence of multiple components is due to measurement error, sales or substitutions, the high variance of structural sector-specific shocks in stylized fact *(i)* is substantially overestimated by simple factor models. Rather, the refined factor model estimates sectoral shocks to be three to four times as volatile as aggregate shocks for the median sector, substantially lower than the nine times more volatile in the simple factor model. Importantly, heterogeneity across sectors is large. We find that aggregate shocks are more important than sector-specific shocks for one sector in four. Both the micro literature and model validation tests support the plausibility of measurement errors, sales and substitutions as the underlying cause of the additional components.

7 Robustness

The main results of the benchmark model go through for other data sets and for variations in the model specification considered. First, as in Boivin et al. (2009), we consider the effect of shortening the sample period to 1984-2005. This serves to isolate the results from the very different behavior of macroeconomic aggregates prior to and during the early eighties disinflation and the start of the so-called Great Moderation. Figures 7 and 8 document the variance and persistence of the various components for this period. Compared to the full sample results documented in Figure 6 the relative variance of aggregate shocks is substantially smaller already in the simple model. This is not unexpected, since decreased variance of aggregate conditions is exactly what the Great Moderation represents. Comparing the relative importance of aggregate shocks in the simple factor model with that of the benchmark model, which accounts for sales and substitutions, again shows how the former model substantially overestimates the relative importance of the sector-specific component. While the traditional approach suggests that in the median sector idiosyncratic shocks are roughly 14 times more important than aggregate shocks, the benchmark model finds this to be only 6 times as large. One could argue that this high relative variance of idiosyncratic shocks was particular to the Great Moderation era and might well disappear when considering more recent data.[16] Turning to persistence in Figure 8, the results for the subsample are very similar to those for the full sample. A simple factor model reveals no persistence due to sectoral shocks for the median sector, while substantial persistence is visible in the model that accounts for measurement error, sales and substitutions. Again, one observes the strong concentration of sectors at very high levels of persistence.

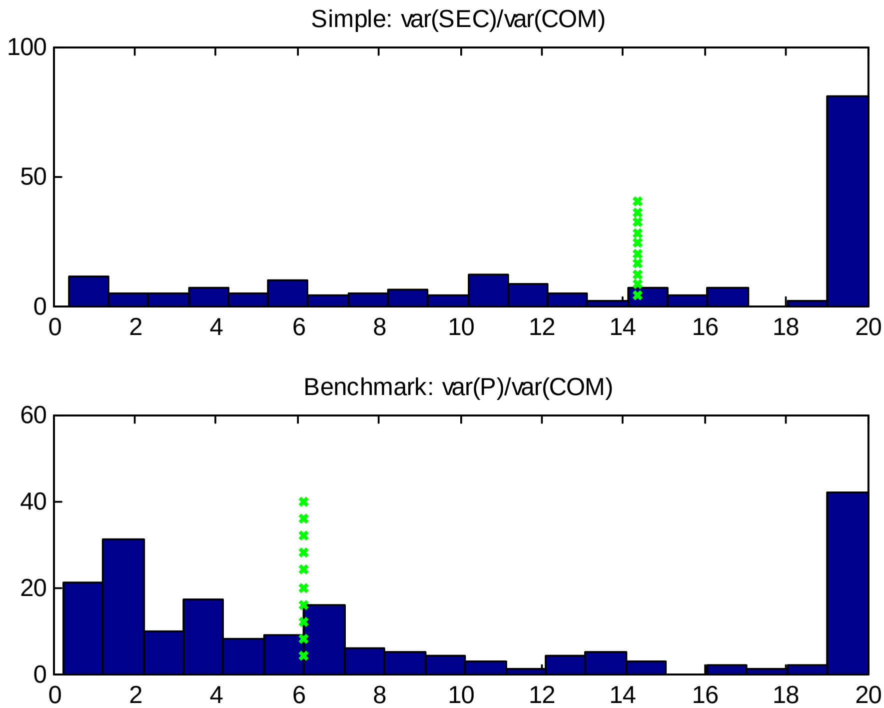
Second, to assess the generality of their results, Boivin et al. (2009) also consider sectoral PPI series, and document that the stylized facts continue to hold. As an additional robustness check, we therefore re-estimate the simple model and the benchmark factor model for the PPI data. Here too, the results are very similar: The simple model confirms the first stylized fact and estimates sectoral shocks to be 9 times more volatile than aggregate shocks for the median sector (Figure 9). The benchmark model reduces this ratio to below 4. In terms of persistence, too, a similar bias appears to be present. As is clear from Figure 10, the standard, simple approach finds no persistence – stylized fact *(ii)* – while the benchmark approach indicates substantial persistence.[17]

Third, we now switch from documenting robustness in terms of data to robustness in terms of model specification. Recall that our sales definition, operationalized by eq. (8),

[16] Unfortunately, a change in the PCE definition makes extending the sample and verifying this conjecture infeasible.

[17] Micro price studies show that sales are rather uncommon in producer prices. On the one hand, this may reduce the likelihood of the M-component to capture sales, but rather e.g. measurement error. On the other hand, a lower incidence of sales at the micro-level can also reduce the likelihood of them aggregating out at the sector-level, in which case M would absorb sales.

Figure 7: Variance - subsample



is the most restrictive among the alternatives in the literature, possibly not capturing all sales in the data. We therefore also explore a less restrictive sales definition that replaces eq. (8) by

$$M_{it} = \rho_{m,i}(L)M_{it-1} + \xi_{it}$$

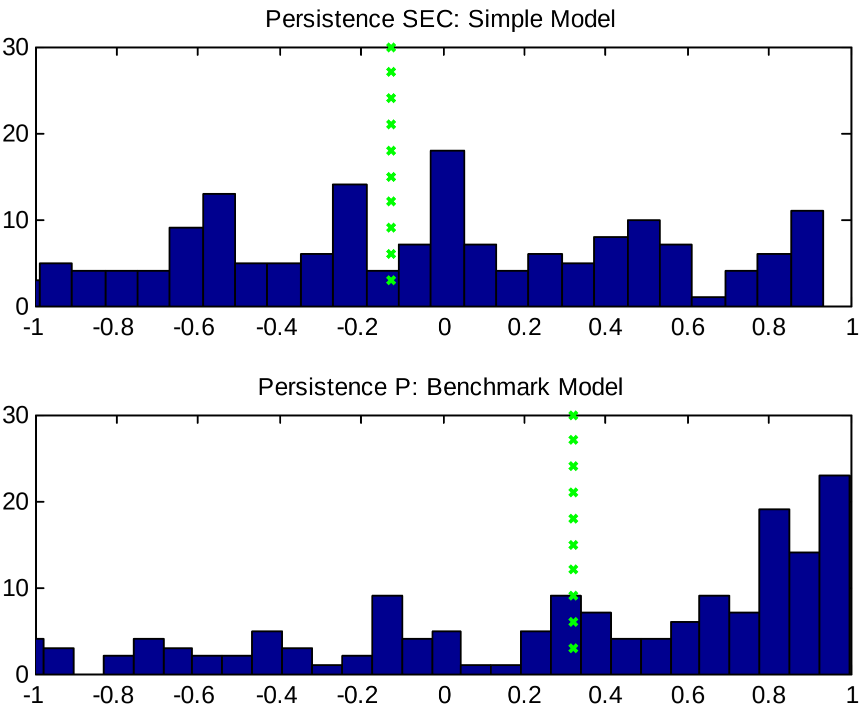
and where identification is achieved by restricting the sum of the lags to be negative, $\rho_{m,i}(1) < 0$, while for the persistent component, P_{it}, we require $\rho_i(1) > 0$. Also this alternative specification yields very similar results to our benchmark model, both in terms of volatility of each component and persistence of P_{it}.

Finally, we perform a robustness exercise where we reduce the lag length of the persistent component, P_{it}. The reason for this exercise is that 13 lags may over-parameterize the model, in particular in the presence of the two additional components. The results are very similar to our benchmark specification when either imposing 3 lags or using standard lag selection criteria.

8 Conclusion

A refinement of the simple factor model reveals that sector-specific shocks do generate persistent inflation responses. This implies that stylized fact *(ii)* is not a robust feature of

Figure 8: Persistence - subsample

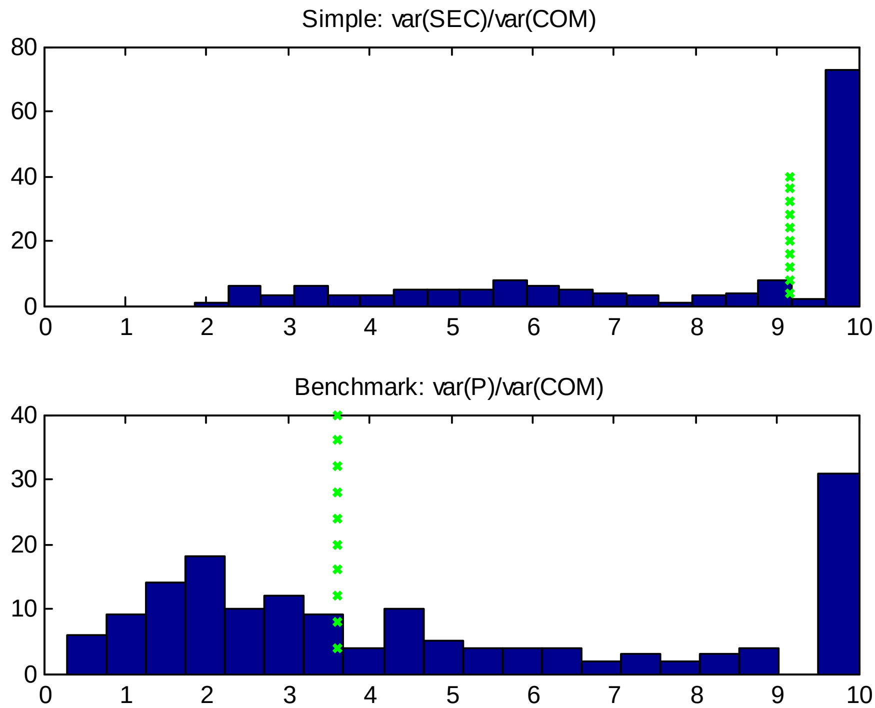


the data. It should therefore not be used to validate theoretical models of price rigidity.

One possible explanation which is both plausible on a priori grounds and supported by model validation exercises, is that sector-specific high-frequency fluctuations are caused by measurement error, sales and substitutions. If that is the case, our estimates point to a ratio of sector-specific to aggregate volatility of three to four for the median sector. Moreover, heterogeneity prevails: for a quarter of the sectors in our data, aggregate shocks appear to be a more important source of fluctuations than sector-specific shocks.

The evidence presented in this paper brings the micro and macro evidence on sluggishness closer together. Initially, high frequency volatility in sectoral price series seemed puzzling from the perspective of inflation inertia at the macro level. Boivin et al. (2009) reconciled this (non-filtered) fast-micro and slow-macro evidence by invoking conditionality: it matters whether a shock is aggregate or sector-specific. Our results, by contrast, reveal that there is no conflict between the micro and macro evidence: Applying filters similar to those used in research on micro (product-level) price data, thereby taking account of measurement error, sales and substitutions, one obtains very similar results. Lower volatility and higher persistence are obtained when sales and substitutions are accounted for. This is apparent from micro studies such as Nakamura and Steinsson (2008), Kehoe and Midrigan (2012) and Eichenbaum et al. (2011) as well as from our benchmark

Figure 9: Variance - PPI



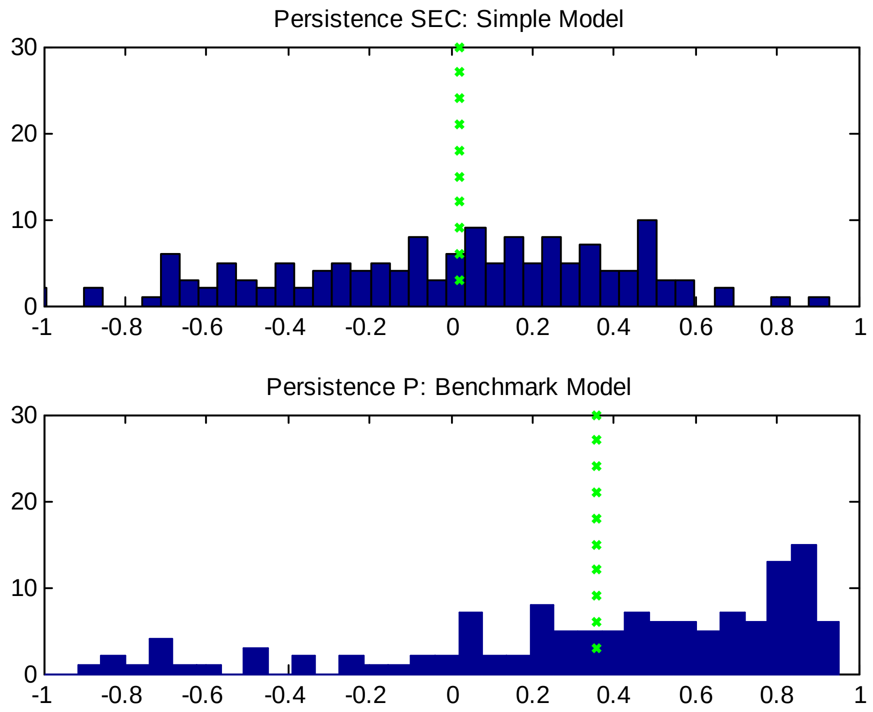
factor model. Furthermore, such findings contrast starkly with those obtained for non-filtered data, at both micro and macro level. In particular, non-filtered prices appear very volatile, and have low persistence. This is evident from the simple factor model (Boivin et al., 2009) and micro studies that do not control for sales (e.g. Bils and Klenow, 2004).

Our findings have important implications for model calibration and validation. As discussed in Maćkowiak and Smets (2009), models of rational inattention (Maćkowiak and Wiederholt, 2010) and menu costs (Golosov and Lucas, 2007), for instance, often rely on sector-specific shocks that are an order of magnitude larger than aggregate shocks. Our refined factor model suggests that this is not necessarily what sectoral price data convey. Instead, in one quarter of all sectors aggregate shocks are a more important source of fluctuations than sector-specific ones.

In light of the above evidence, models of price rigidities should not be refuted because they fail to generate a sluggish response to aggregate shocks and a fast response to idiosyncratic disturbances. Persistence occurs in response to both aggregate and sectoral shocks. Finally, there is a tremendous amount of heterogeneity between sectors in these findings, again consistent with the micro-evidence (Nakamura and Steinsson, 2008).

The results of the present paper also have implications for the appropriate design of core inflation indices. The fact that sector-specific dynamics are best characterized as

Figure 10: Persistence - PPI



multicomponent processes means that sectors should not be excluded from a core index based on simple statistics such as unfiltered persistence or volatility.[18] Such exclusion-based core measures are commonly used by central banks, most explicitly by Bank of Canada. The Federal Reserve's motivation for focusing on PCE inflation excluding food and energy is a related short-cut in that direction.

[18] Dolmas (2009) also concludes that simple filters mask important underlying persistence and discusses implications for core inflation indices.

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Appendix A: Estimator properties in finite samples of simulated data

This appendix documents empirical properties of the maximum likelihood estimator used in the paper. We also quantify the bias from estimating an AR process when the DGP consists of multiple components. In particular, we simulate data from various one- and multicomponent processes for sample lengths equal to our data ($T = 353$). For each of these, we estimate single component (P, as in eq. (4), henceforth AR) and multicomponent processes ($P + I + M$, as in eq. (5)-(8), henceforth PIM). For each process we use one lag for the AR (P) component. The Monte Carlo results are based on 100 time series per data-generating process. The data is generated from

$$e_t = P_t + I_t + M_t$$

with

$$\begin{aligned} P_t &= \rho P_{t-1} + \varepsilon_t \\ I_t &= \epsilon_t \\ M_t &= \xi_t - \xi_{t-1} \end{aligned}$$

for the parameter values in Table 8.

Table 8: Data generating processes for artificial data

	IID	AR low	AR high	PIM low	PIM high
ρ	0	0.5	0.95	0.5	0.95
σ_P^2	1	1	1	.33	.33
σ_I^2	0	0	0	.33	.33
σ_M^2	0	0	0	.33	.33

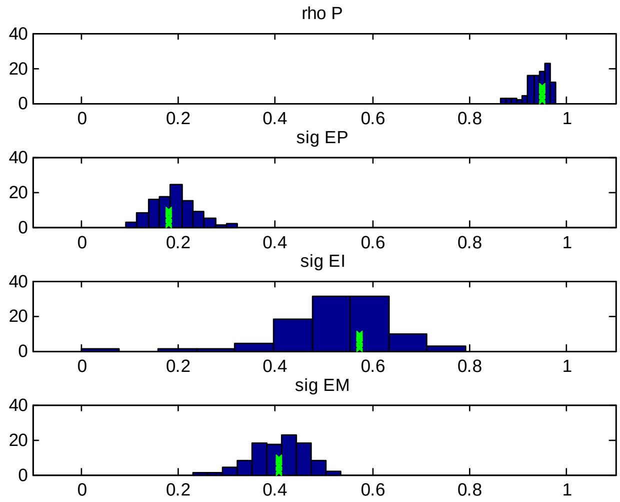
Note: To facilitate evaluation of the relative importance of the various components, the table specifies volatility of the components rather than the innovations. Thus, $\sigma_P^2 = \frac{\sigma_\varepsilon^2}{1-\rho^2}$, $\sigma_I^2 = \sigma_\epsilon^2$, $\sigma_M^2 = 2\sigma_\xi^2$ and the three shocks are orthogonal and follow $(\varepsilon_t, \epsilon_t, \xi_t)' \sim N(0_{3\times1}, D)$.

Consider the last column of Table 8, PIM high. Here all three components are equally important, and the persistent component is very persistent. Figure 11 shows how, even for data with a limited time dimension, the estimator has no problem disentangling the various components.

It is plausible that high persistence makes identification easier. Therefore, now consider a PIM process with intermediate persistence, PIM low in Table 8. In this case, as apparent from Figure 12, there is more dispersion in point estimates. Persistence tends to be slightly underestimated (and, accordingly, the volatility of the persistent shock slightly overestimated). The M component is still consistently identified, while the I component is not always easily detected.

Now consider the alternative; estimating an AR specification on these data. Irrespec-

Figure 11: Estimation on simulated data: PIM on PIM high

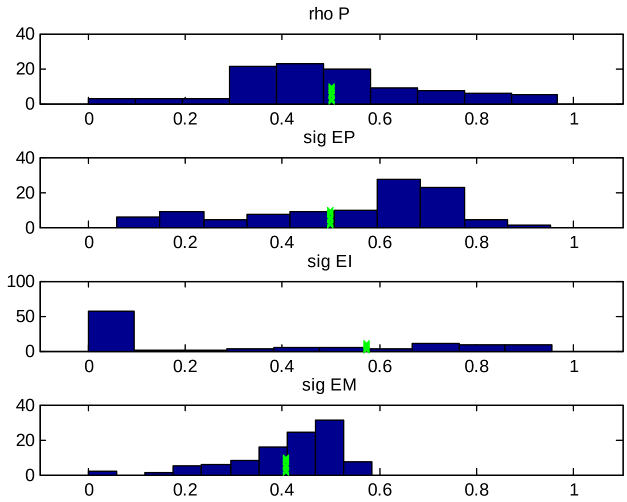


Note: Green x's mark data-generating parameters

tive of the persistence of the underlying process, estimating an AR fails to detect any significant amount of persistence, as illustrated in Figure 13 and Figure 14. We interpret these simulations as follows. While for low-persistence multicomponent processes, PIM-specifications may imply substantial imprecision regarding the variances of the components, they allow a fairly adequate evaluation of persistence. When persistence is high, they are both unbiased and precise across repeated samples, for the empirically relevant sample lengths. For the same DGP's, AR-specifications are clearly inadequate. These simulations establish one type of risk: if the DGP is a multicomponent process, AR estimation will fail to detect persistence.

The question remains as to how PIM-specifications perform in the case of AR-DGPs. It is possible that the cure is worse than the disease. Figure 15 shows that this type of risk is limited. In particular, for an AR-DGP with high underlying persistence estimating a PIM-specification comes at little cost. As persistence decreases, see Figure 16, PIM-estimation attributes some variation to the I component, which entails a minor overestimation of persistence. Taken to the limit, estimating PIM-specifications on *iid* data, as in Figure 17, identification of separate components is cumbersome: there is a lot of dispersion in all the estimates. Firstly, however, note that the modes of the distributions are typically located at the truth. Secondly, for persistence close to zero, the likelihood is flat in certain dimensions. This occurs as P and I become equivalent and is further discussed in footnote 7 in the main text.

Figure 12: Estimation on simulated data. PIM on PIM low



Appendix B: Isolating measurement error using quantities

The observation equation for sector i becomes

$$\pi_{it} = \lambda_i^{\pi\prime} C_t + P_{it} + I_{it} + M_{it} + \eta_{it} \tag{9}$$

$$q_{it} = \lambda_i^{q\prime} C_t + \alpha_i^P P_{it} + \alpha_i^I I_{it} + \alpha_i^M M_{it} + \varsigma_{it}. \tag{10}$$

or

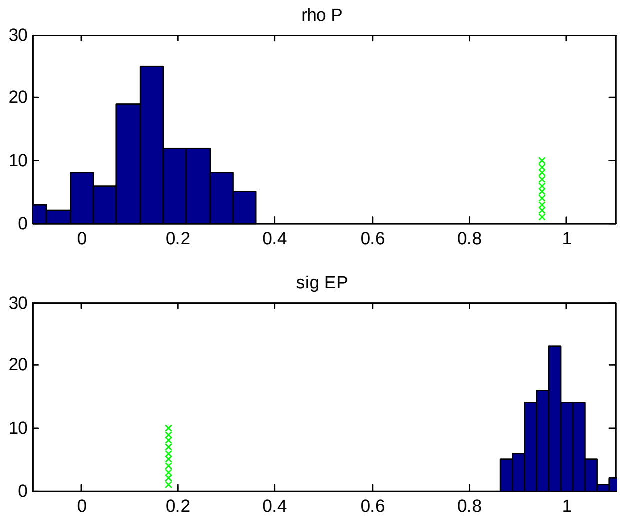
$$\begin{bmatrix} \pi_{it} \\ q_{it} \end{bmatrix} = \begin{bmatrix} \lambda_i^{\pi\prime} \\ \lambda_i^{q\prime} \end{bmatrix} C_t + \begin{bmatrix} 1 & 1 & 1 \\ \alpha_i^P & \alpha_i^I & \alpha_i^M \end{bmatrix} \begin{bmatrix} P_{it} \\ I_{it} \\ M_{it} \end{bmatrix} + \begin{bmatrix} \eta_{it} \\ \varsigma_{it} \end{bmatrix}$$

Here q denotes quantity growth. In addition to the requirement that the three components P, I and M affect quantities, their persistence properties continue to hold, as in eqs. (6)-(8). Measurement error in inflation and quantity growth are denoted by η_{it} and ς_{it} respectively. They are identified because they affect price or quantity respectively, but not both.

In the PCE data used by Boivin et al. (2009) real quantities are available, as part of X_t. However, real quantities are not measured independently, but calculated as nominal quantity deflated by the price index. To ensure that measurement error does not affect the quantity variable we therefore use nominal quantities.

In eq. (9), as before, the I and M components absorb substitutions and sales, respectively. The importance of measurement error is now captured separately by the sector-specific component η_{it}. Note that substitutions related to sampling (a product not being available at the surveyed retailer) will not be captured by the I component in this

Figure 13: Estimation on simulated data. AR on PIM high



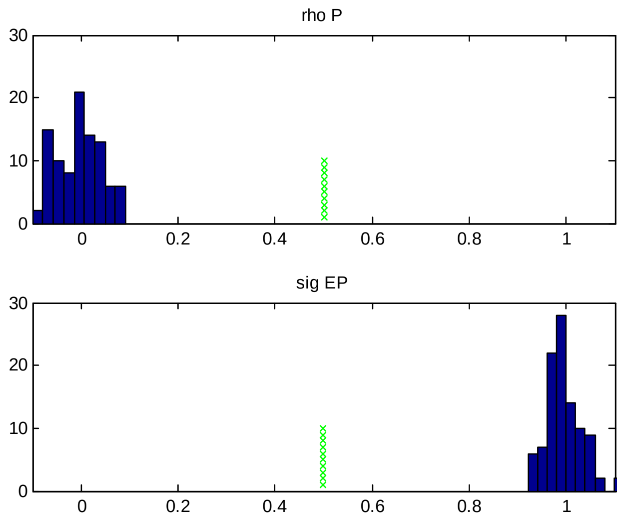
setting, but instead by the measurement error component for inflation, η_{it}.

We allow both the idiosyncratic inflation and quantity components η_{it} and ς_{it} to exhibit unrestricted autoregressive dynamics. The reason for this flexible specification is that, for the inflation equation, for instance, measurement error in prices would generate negative autocorrelation.

Note that the identification assumption that the P, I and M components affect quantities does not hold at $\alpha_i^{\cdot} = 0$. This case does not turn out to be practically important. We have also estimated Bayesian versions where the sector-specific loadings are identified through the prior, with very similar results.

Table 7 in the main text summarizes the results of estimating (9)-(10), subject to (6)-(8). The following figures show the results for the relative variance (Figure 18) and persistence (Figure 19). They are very similar to the results of the benchmark factor model presented in the main text.

Figure 14: Estimation on simulated data. AR on PIM low



Appendix C: Aggregation

Since sectoral price indices are combining price quotes across multiple cities, stores and products, one might expect sales, substitutions and general measurement error to average out at the sectoral level. While there definitely is scope for aggregation to reduce the need for our additional components, there are a number of elements that reduce the tendency of these components to be aggregated away at the sector level and at the sampled (monthly) frequency. In what follows, we first discuss aggregation under ideal conditions – uncorrelated homogenous-size price changes. We then discuss and quantify two aspects that decrease the power of aggregation: correlated sales or substitutions and heterogeneity in the size of price changes. Throughout we make the simplifying assumption that all products receive equal weights in the sector-level indices.

The discussion below concerns what fraction of the volatility of product-level sales and substitutions remains at the sector level. But let us start by stating that the dynamics, in particular the persistence properties, induced by these phenomena remain unchanged by aggregation: An *iid* movement induced by substitution at the product level induces an *iid* movement in the corresponding sector index. Similarly for the MA component induced by sales.[19]

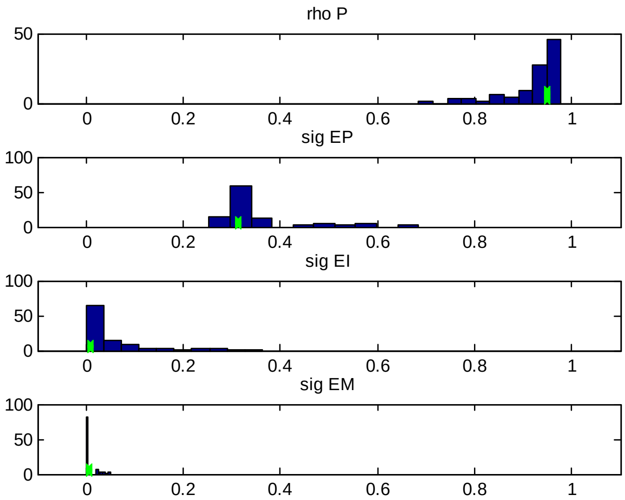
The first reason product level measurement errors do not completely cancel out at the sectoral level is that the number of product prices sampled per month is limited. The

[19]Recall eq. (8), which at the sector level yields

$$M_{it} = \sum_j (\xi_{jit} - \xi_{jit-1})$$

where j indexes products within a sector and ξ_{jit} is uncorrelated across t. Then $Var(M_{it}) = 2Var(\xi_{ji})$

Figure 15: Estimation on simulated data. PIM on AR high



consumer price index (CPI), which is the main source of the sectoral PCE price indices we use, is based on 70.000-80.000 prices across 388 entry-level items (ELIs) roughly corresponding to the PCE sectors we study, yielding a mean number of observations slightly above 200 product prices per ELI/PCE sector and month. Theoretically, in absence of any aggregation problems, the ratio of the standard deviation of the index, σ_{index}, to the standard deviation of the product price, $\sigma_{product}$, is $\frac{1}{\sqrt{N}}$. This implies that for the sector with the mean number of observations $1/\sqrt{200} = 7\%$ of the variation induced by sales and substitutions at the product level would remain at the sector level.[20] The first column in Table 9 present the corresponding numbers for the empirically relevant range of sample sizes.

Correlated sales or product substitutions could occur due to sector-specific shocks:

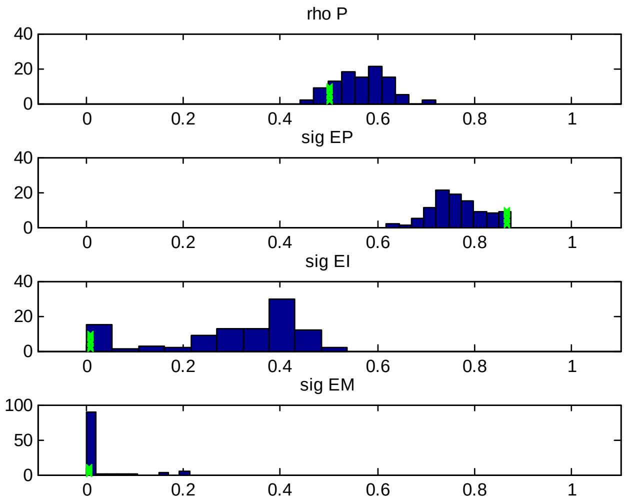
and autocorrelation at the sector level is

$$
\begin{aligned}
\rho\left(M_{it}, M_{it-1}\right) &= \frac{1}{Var(M_{it})} Cov\left(\sum_j \left(\xi_{jit} - \xi_{jit-1}\right), \sum_j \left(\xi_{jit-1} - \xi_{jit-2}\right)\right) \\
&= \frac{1}{Var(M_{it})} Cov\left(\sum_j \left(-\xi_{jit-1}\right), \sum_j \left(\xi_{jit-1}\right)\right) = \\
&= -\frac{Var\left(\sum_j \xi_{jit-1}\right)}{Var(M_{it})} = -0.5
\end{aligned}
$$

which coincides with the product-level autocorrelation of M_{jit}.

[20] Whether that 7% represents a large fraction of the index's variance, which also contains regular price changes, is a different question. It depends on the relative volatility of sales and substititions vs. regular price changes at the product level. Micro level data suggest that sales and to a smaller degree, substitutions, may well cause substantially more volatility than regular price changes (see Section 4 for details). This makes effectively controlling for them at the index level all the more needed.

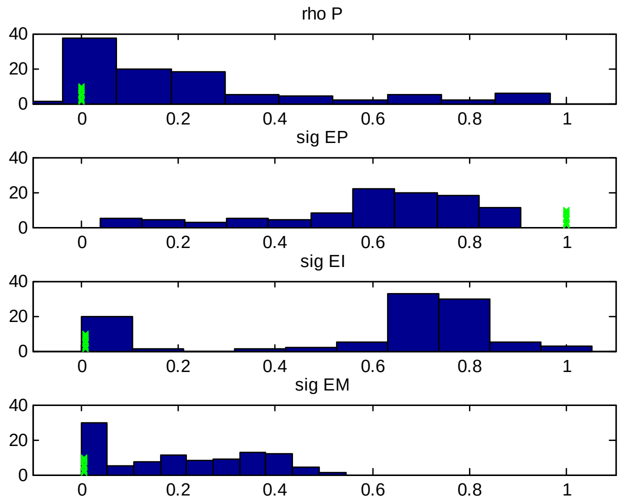
Figure 16: Estimation on simulated data. PIM on AR low



low demand can build up inventory and induce larger sales, technical progress can generate product turnover and induce product substitutions, etc.[21] To illustrate the impact of correlated sales or substitutions we perform the following exercise. For a sample length equal to ours (T=353) we randomly generate sequences of sales (the outcomes are indistinguishable for the case of substitutions). At any point in time, an individual product is on sale with a particular frequency. If there is no sale, the price remains constant. When there is a sale, the price change is a sum of two random components from the normal distribution: A common component generates correlated variation across products within an index and an idiosyncratic component generates uncorrelated variation. We generate many product level price series, and construct inflation indices from them, for a variety of numbers of goods in the index, N. In this exercise the only reason that the theoretical prediction of the effect of aggregation, $1/\sqrt{N}$, does not obtain is that the size of sales contain a common component that makes them correlated. We let the correlation equal 0.25. In Table 9 we present the results for a range of frequencies, recalling from Section 4 that micro evidence indicates that the median monthly frequency of sales are in the range from 7.4% to over 20%, and 3.4% to 5% for item substitutions. The first, and least surprising, result to note is that correlated sales do not aggregate away very well. Secondly, aggregation actually works better the lower the frequency is. The intuition is that for low frequencies the realized correlation tends towards zero as most prices are unchanged. To specifically address the question of how well aggregation works for the median sector, we read from the table that for $N = 200$, the ratio of the standard deviation of the index

[21] Note that the price data we work with is seasonally adjusted, so correlation in sales that follow a seasonal pattern are filtered out.

Figure 17: Estimation on simulated data. PIM on iid



relative to the standard deviation of its underlying products $\frac{\hat{\sigma}_{index}}{\sigma_{product}}$ is roughly 0.2 at the empirical frequency of sales and roughly 0.1 at the empirical frequency of substitutions. Interestingly, results at the empirical frequency of sales are approximately unchanged for $N = 500$ and $N = 1000$. In other words, roughly 20% (10%) of the product level volatility from sales (substitutions) remains at the sector level if correlation is 0.25. This is substantially more than for uncorrelated price changes.

Table 9: Aggregation and sales/substitutions - correlation

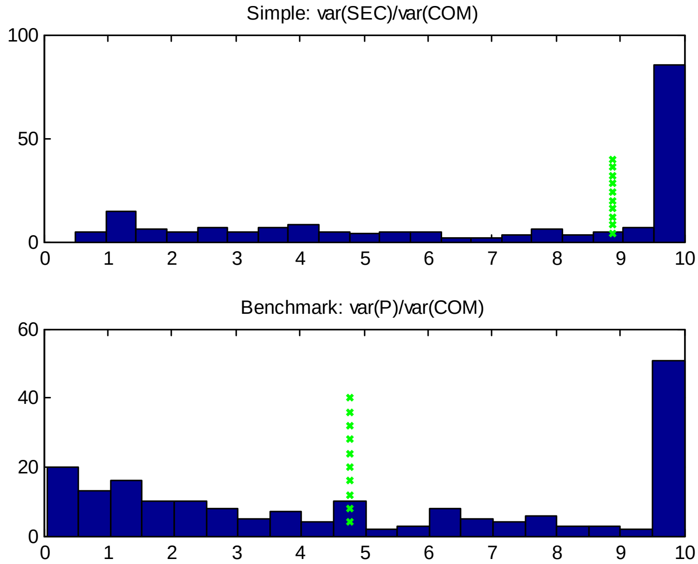
		Frequency			
Number of products in index: N	$1/\sqrt{N}$	0.25	0.1	0.05	0.01
50	0.1414	0.2849	0.2110	0.1796	0.1495
100	0.1000	0.2685	0.1865	0.1497	0.1113
200	0.0707	0.2595	0.1728	0.1319	0.0864
500	0.0447	0.2536	0.1640	0.1205	0.0670
1000	0.0316	0.2519	0.1611	0.1162	0.0591

Note: The table reports the ratio of the standard deviation of an index, $\hat{\sigma}_{index}$, relative to the (homogenous) standard deviation of its underlying products, $\sigma_{product}$, for various N and frequencies, but for a fixed correlation of 0.25. The first column is the theoretical relation without correlation and the four subsequent columns the small-sample (T=353) results across 5000 replications.

It is plausible that not all products within a sector exhibit the same unconditional size of sales or substitutions. Heterogeneity in size of sales or substitutions within a sector weakens aggregation. Intuitively, the degree to which various sales or substitutions cancel out at the sector level decreases with size heterogeneity.

To quantify the effect of heterogeneity we perform a similar exercise to the one above. We let the size of the sale or substitution be a random draw from a normal distribution

Figure 18: Identification using quantities - variance



whose standard deviation is drawn from a uniform distribution to induce heterogeneity in size. As a rough reference for the within-sector size heterogeneity we use heterogeneity between major groups from Nakamura and Steinsson (2008). It shows that the standard deviation of the sales size, σ_{size}, is one third of the mean sales size, μ_{size}, for both of the sample periods they report.

We report the results for a range of heterogeneity in Table 10. We note that the quantitative impact of heterogeneity in size is limited for this range of heterogeneity. Results are indistinguishable for sales and substitutions, and independent of frequency.

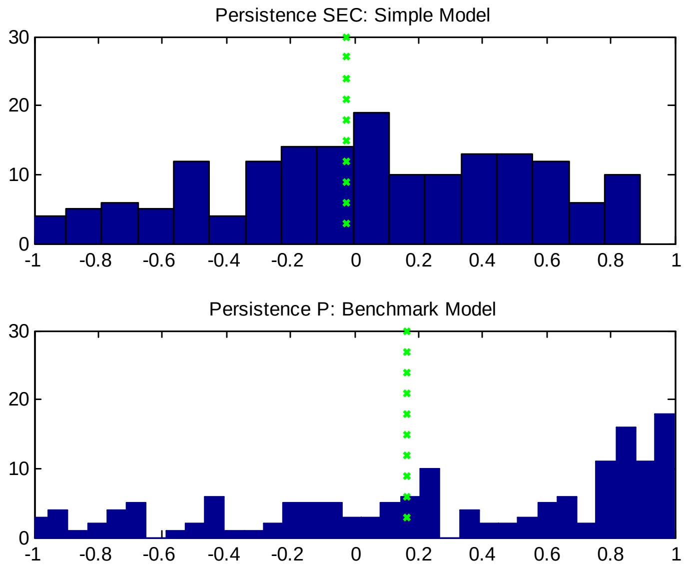
Table 10: Aggregation and sales/substitutions - heterogeneity

		σ_{size}/μ_{size}				
Number of products in index: N	$1/\sqrt{N}$	0.95	0.75	0.5	0.25	0.05
50	0.1414	0.1952	0.1761	0.1577	0.1456	0.1416
100	0.1000	0.1376	0.1247	0.1118	0.1031	0.1000
200	0.0707	0.0973	0.0882	0.0790	0.0728	0.0707
500	0.0447	0.0616	0.0558	0.0500	0.0460	0.0447
1000	0.0316	0.0436	0.0395	0.0353	0.0325	0.0317

Note: The table reports the ratio of the standard deviation of an index, $\hat{\sigma}_{index}$, relative to the mean of the heterogenous standard deviation of its underlying products, $\sigma_{product}$, for various ratios of the within sector standard deviation of the size of sales, σ_{size}, to the mean size of sales, μ_{size}. The first column is the theoretical relation without heterogeneity, the four subsequent columns the small-sample (T=353) results for lower frequencies of price change across 5000 replications.

In this section we have quantified how much of product-level variation in prices due to sales and substitutions remains at the sector-level. We first noted that the empirical

Figure 19: Identification using quantities - persistence

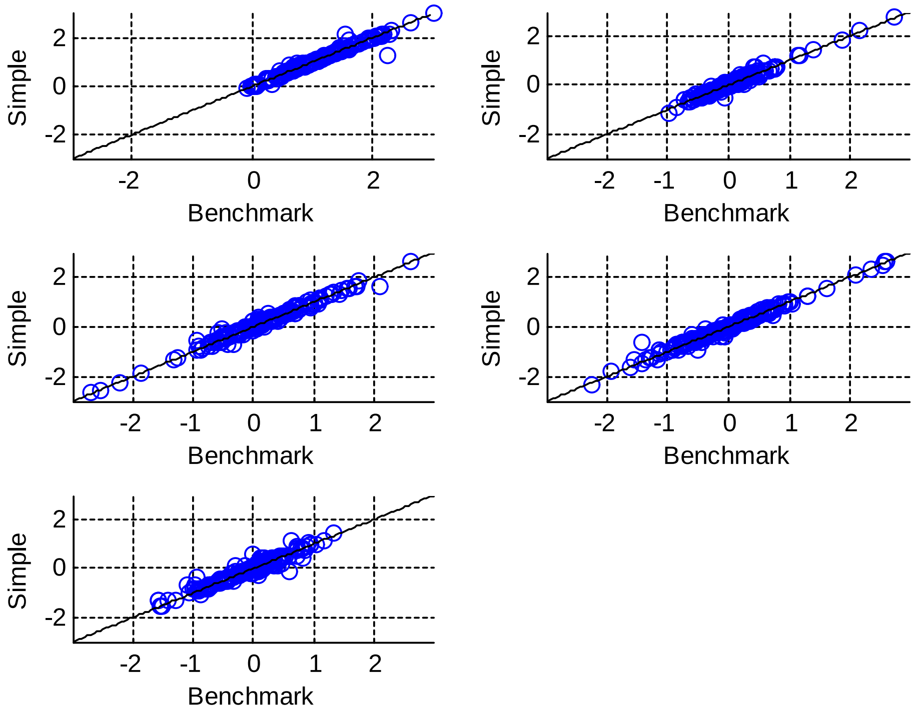


sample size in the mean sector is limited. This makes it likely that sales and substitutions generate significant variance at the sectoral index level. We then separately quantified the impact of two factors that further weaken aggregation: correlation and heterogeneity. Empirically, across sectors, there are different numbers of products per sector, varying degrees of heterogeneity across products within each sector, and varying degrees of correlation between those products. Each of these factors, and possible interactions between them affect how well aggregation works.

Appendix D: Comparison of factor loadings - benchmark vs. simple

Figure 20 compares the estimated loadings for 190 PCE sectors on common factors of the benchmark model (with 3 sectoral components) and the simple model (with one single sectoral component). Correlations are 0.99 except for the last factor with correlation 0.97.

Figure 20: Loadings on the 5 common factors.



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