Evidence on the effects of inflation on price dispersion under indexation*

by Juliane Scharff and Sven Schreiber†

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Abstract

Distortionary effects of inflation on relative prices are the main argument for inflation stabilization in macro models with sticky prices. Under indexation of non-optimized prices those models imply a nonlinear and dynamic impact of inflation on the cross-sectional price dispersion (relative price or inflation variability, RPV). Using US sectoral price data we estimate such a relationship between inflation and RPV. We confirm the impact of inflation fluctuations but find hitherto neglected endogeneity biases, and our IV and GMM estimates indicate that average ("trend") inflation is significant for indexation. Lagged inflation is less important.

Keywords: relative price variability, trend inflation, endogeneity bias

JEL codes: E31 (inflation), C22 (single-equ. time series)

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†Scharff: Halle Institute for Economic Research (IWH); Schreiber (corresponding author): Goethe University Frankfurt, and Macroeconomic Policy Institute (IMK) at Hans Boeckler Foundation, Hans-Böckler-Str. 39, D-40476 Düsseldorf, Germany, fax +49(0)211-7778-4332, e-mail svetosch@gmx.net.

1 Introduction

In this paper we analyze the impact of inflation on the cross-sectional dispersion of prices (relative price variability, RPV) in the USA. In modern business cycle models with nominal price rigidities ("New Keynesian" models) the distortionary effect of inflation on relative prices is the main argument for inflation stabilization, see Woodford (2003). For monetary policy it is therefore important to gauge the empirical relevance of this effect and to learn how exactly inflation developments are transmitted to the RPV.

The empirical RPV literature has a long tradition and is extensive,[1] but in our view there is room for improvement along the following dimensions: First of all we allow for the realistic possibility that firms which do not optimize their prices in a given period raise their prices using some constant rate –possibly the average ("trend") inflation rate– or using the latest observed inflation rate.[2] This broader framework implies that the RPV-inflation relation is of a dynamic nature and inherently nonlinear, which for example may imply that gradual instead of sudden inflation adjustments could be the best response to past inflation deviations (in the sense of minimizing RPV). Furthermore we believe that the existing literature has not taken sufficiently into account the fact that the general level of inflation cannot be regarded as an exogenous variable.[3] We show that the resulting endogeneity bias is empirically relevant and present new estimates using appropriate instrumental-variables techniques (including GMM).

Our results are based on two intersectoral price datasets for the US. The first one is composed of roughly 100 sectoral subaggregates of the producer price index (PPI), whereas the second one uses about 25 consumer price index (CPI) categories. For both datasets our results broadly confirm the general finding of an economically detrimental

[1] See for example Parks (1978), Bomberger and Makinen (1993), Reinsdorf (1994), Grier and Perry (1996), Parsley (1996), Fielding and Mizen (2000), Silver and Ioannidis (2001).

[2] Similar assumptions appear in Smets and Wouters (2003), Christiano, Eichenbaum, and Evans (2005) and many recent followers.

[3] The endogeneity of inflation becomes most apparent in another strand of the literature where price dispersion is the explanatory variable that affects inflation, see for example Gerlach and Kugler (2007).

effect of inflation on RPV.[4] However, given the history of positive average inflation we find that under the current pricing behavior of firms RPV is minimized for low but positive levels of inflation.

While we employ a novel estimation approach, there are of course other recent strands of the literature that analyze the RPV-inflation relationship in dynamic settings.[5] For example, Parsley (1996) and Nath (2004) estimate bivariate VARs that include inflation and RPV; such a specification is somewhat at odds with theory, however, because in a linear VAR a positive RPV response with respect to a positive money supply shock implies a negative response with respect to a negative shock. In contrast, most theoretical models posit that positive as well as negative monetary shocks should increase RPV. In terms of dynamics the specification of Fielding and Mizen (2000) is related to ours, but they do not test the possible endogeneity of the inflation rate. Grier and Perry (1996) use a model where lagged RPV, lagged squared inflation and the conditional variance of inflation all affect RPV. They explicitly state that they use lagged squared inflation to avoid the endogeneity problem, but the endogeneity status of the conditional inflation variance remains dubious. There is also a recent literature where the marginal impact of inflation depends on the inflation level in a different way than a second-order polynomial of inflation: Bick and Nautz (2008) use threshold models with low, intermediate, and high inflation regimes (but use a static relation), whereas Fielding and Mizen (2008) fit a non-parametric smooth-transition function. [6]

[4]This statement refers to specifications where either RPV is measured as the variance and is regressed on squared inflation, or RPV is measured as the standard deviation and is regressed on the absolute value of inflation. Although the latter regression equation is not strictly equivalent to the former because of the additive constant and residuals, results tend to be similar. It is worthwhile noting that this finding is mathematically compatible with a negative sign in a regression with RPV measured as the coefficient of variation as in Reinsdorf (1994) or Silver and Ioannidis (2001), so attention must be paid to the precise specification when interpreting the sign of the coefficient of inflation.

[5]It seems adequate to also mention Silver and Ioannidis (2001) although they do not consider a dynamic setup. They perform a cross-country comparison and control for many other macroeconomic factors; however, in light of the large number of contemporaneous variables on the right-hand side it is surprising that they do not check for endogeneity problems.

[6]The importance of inflation regimes on the relation between inflation and RPV is also emphasized by Ahlin and Shintani (2007). They show that firms' optimal pricing entails using different (s,S) bands in

Another approach in the literature consists of using impulse-response analysis in VAR systems that include individual commodity prices to measure the impact of monetary policy shocks on the cross-sectional distribution of prices, see Bils, Klenow, and Kryvtsov (2003), Lastrapes (2006), or Balke and Wynne (2007). This multi-price VAR approach is a useful and promising alternative approach to the single-equation analysis of the standard RPV literature. As always in VAR analysis, however, it is crucial to identify the monetary shock correctly in order to get meaningful results, and how to identify a monetary shock is a matter of ongoing research and controversy, apart from the fact that systematic monetary policy is not covered in a shock-based VAR framework. In our nonlinear setup there are also additional channels where the (time-average) variance and autocovariance of inflation may matter.

The structure of this paper is straightforward: In section 2 we derive the estimated equation, we discuss its interpretation, and we explain our estimation approach. In section 3 we present some characteristics of the datasets that we use, and in section 4 we report the details of our specifications and the results of our analysis. Section 5 offers conclusions.

2 The framework

2.1 Specification and interpretation

The traditional approach in the RPV literature can be summarized in the following bivariate regression:

$$rpv_t = b_0 + b_2 \pi_t^2 + u_{b,t} \tag{1}$$

where typically a positive coefficient for squared inflation is found when estimating this equation by OLS.[7]

high-inflation and low-inflation states of the world. The data from Mexico's tequila crisis confirm their theoretical results.

[7] Closely related is another widespread specification with the root of RPV as dependent and the absolute value of inflation as the explanatory variable.

In contrast, consider equation (2.24) from Woodford (2003) as a reference for a more general framework:

$$rpv_t = \alpha rpv_{t-1} + \frac{\alpha}{1-\alpha}(\pi_t - \gamma\pi_{t-1})^2, \tag{2}$$

which is derived from Calvo pricing with some degree of backward-looking indexation by those firms who are assumed to be non-optimizing in the given period. In the simple theoretical model the parameter α is the fixed proportion of non-optimizing firms, and γ is the degree of indexation. As a starting point for our analysis we generalize this equation in several directions:

- We add a constant term inside the squares term to account for positive average inflation in general and accordingly for some fixed element in the indexation rule, as opposed to the theoretical steady-state value of zero inflation.[8]
- Given that we use inter-sectoral price data we must depart from the theoretical restriction linking the coefficients of lagged RPV and the squared term through the single parameter α and instead we let those coefficients vary freely. However, while the estimated coefficient of lagged RPV may preserve some resemblance to the underlying fraction of non-optimizing firms, the empirical coefficient of the squared term should not be expected to be close to $\alpha/(1-\alpha)$, because the scale of the RPV measure is essentially arbitrary.

Altogether, and after adding a general constant term to reflect the re-scaling of the included variables, our baseline specification reads as follows:

$$rpv_t = c_0 + c_1 rpv_{t-1} + c_2(\pi_t - c_3\pi_{t-1} - c_4)^2 + u_t, \tag{3}$$

where rpv_t now refers to a standardized RPV measure (de-meaned and with unit variance) to facilitate the comparison of coefficients across datasets, and π_t is observed month-on-

[8] See for example Ascari (2004) for initial work on the problems of non-zero average inflation for business-cycle models.

month inflation expressed in annualized percentage rates. For details of the RPV construction see the data section 3.

Let us use c_π to denote the implicit constant indexation rate by which non-optimized prices are increased on average, and which is given by

$$c_\pi = \frac{c_4}{1-c_3}. \tag{4}$$

From equation (3) it is obvious that the average RPV is minimized when the squared term is zero on average, i.e. if the constant indexation term satisfies $c_\pi = \bar{\pi}$, for any given average inflation rate. However, we do not impose this restriction a priori, for example because imperfect competition in goods markets may induce firms to raise prices only cautiously for fear of losing customers. Instead we let the data speak freely about its value, and we can then test whether it is actually equal to average inflation.[9] Another very interesting hypothesis is whether $c_\pi = 0$, which would mean that firms do not index their prices according to some fixed rate. In that case it would be optimal for monetary policy (in the sense of minimizing RPV) to target zero inflation.[10] Given a positive average inflation rate it seems reasonable to treat this as a one-sided test.

Note that most coefficients are expected to be non-negative (c_2, c_4, c_1), and thus many other significance tests will also be interpreted as one-sided. However, as some slight overshooting behavior in the indexation rule cannot be ruled out a priori, c_3 may be positive or negative as long as its absolute value is smaller than unity for stability reasons. Obviously the traditional bivariate specification is nested in our model by considering the case $c_1 = c_3 = c_4 = 0$. Intermediate cases are also possible, such as irrelevance of past inflation ($c_3 = 0$) or irrelevance of a constant term ($c_4 = 0$) for the indexation rule. There-

[9] Given the joint covariance matrix of the estimators of c_3, c_4 we can construct (asymptotically valid) confidence intervals and test statistics using the delta method.

[10] If $c_\pi > 0$ it may still be optimal to target zero inflation for reasons other than the RPV channel, but then policy makers would need to convince agents to adjust their inflationary expectations and their behavior; in other words, a regime change would be needed then.

fore the data have a chance to indicate whether the dynamic and nonlinear extensions are actually needed.

A slightly different but of course related perspective on the relationship (3) can be offered by taking its expectation, where we use the facts that $\mathsf{Var}(\mathsf{x}) = \mathsf{E}(\mathsf{x}^2) - \mathsf{E}^2(\mathsf{x})$ and $\mathsf{AutoCov}(\mathsf{x},\mathsf{x}_{-1}) = \mathsf{E}(\mathsf{x}\mathsf{x}_{-1}) - \mathsf{E}^2(\mathsf{x})$, and we abstract from small differences due to initial observations by setting $\mathsf{E}(\mathsf{x}_\mathsf{t}) = \mathsf{E}(\mathsf{x}_{\mathsf{t}-1}) = \mathsf{E}(\mathsf{x})$. Some algebra yields:

$$
\begin{aligned}
(1-c_1)\mathsf{E}(rpv) \quad = \quad & c_0 + c_2 c_4^2 + c_2(1+c_3^2)\mathsf{Var}(\pi) \\
& + c_2(1-c_3)^2\mathsf{E}^2(\pi) + 2c_2c_4(c_3-1)\mathsf{E}(\pi) \\
& - 2c_2c_3\mathsf{AutoCov}(\pi,\pi_{-1})
\end{aligned} \tag{5}
$$

Here several things are worth noting: First and foremost, second-order moments of inflation are relevant for the expected level of RPV due to the non-linearity of equation (3). It can be seen that as long as inflation has any impact on RPV at all, i.e. $c_2 > 0$, then the variance of inflation affects RPV positively (i.e., adversely), and the average inflation rate affects RPV as a second-order polynomial. Another implication is that if non-optimized prices are indexed to past inflation rates, then the persistence of inflation as measured by its autocovariance also affects average RPV levels. For the case of a positive value of c_3, higher persistence of inflation means higher predictability of inflation which would reduce average price distortions.

The nonlinear equation (3) must be estimated by nonlinear instrumental-variables or GMM techniques, and we will present the according estimates for the PPI dataset. However, there are two problems that lead us to consider a linearized generalization of (3) as well: First, in a nonlinear setting it is not the case anymore that the least-squares estimator is efficient compared to the instrumental-variable estimator, which means that testing for endogeneity bias with the Hausman test would be impossible. Secondly, in the case of the CPI dataset we encountered numerical problems such that the estimators were clearly unreliable or did not converge. Therefore we also work with the following linearized equation which is more general. In a first step, we multiply out the squared term to arrive at an additive model with nonlinear parameter restrictions:

$$rpv_t = c_0 + c_1 rpv_{t-1} + c_2 \pi_t^2 - 2c_2 c_3 \pi_t \pi_{t-1} - 2c_2 c_4 \pi_t + c_2 c_3^2 \pi_{t-1}^2 + 2c_2 c_3 c_4 \pi_{t-1} + c_2 c_4^2 + u_t$$

Next we generalize this equation by letting the regression coefficients vary freely, yielding the equation that will be used for estimation:

$$rpv_t = a_0 + a_1 rpv_{t-1} + a_2 \pi_t^2 + a_3 \pi_t \pi_{t-1} + a_4 \pi_t + a_5 \pi_{t-1}^2 + a_6 \pi_{t-1} + \varepsilon_t, \qquad (6)$$

where of course $a_0 = c_0 + c_2 c_4^2$, $a_1 = c_1$, $a_2 = c_2$, $a_3 = -2c_2 c_3$, $a_4 = -2c_2 c_4$, $a_5 = c_2 c_3^2$, and $a_6 = 2c_2 c_3 c_4$ should ideally hold, but to be able to apply linear estimation methods we do not impose these restrictions, and therefore deviations from this mapping will happen in practice. In that sense the results should be interpreted with the necessary caution. For a_2 and a_5 we expect positive signs, whereas a negative sign should result for a_4. Since equation (6) contains two more free parameters than equation (3), not all coefficients of the former are expected to be individually significant even if all parameters of (3) are relevant. For example, a_3 and a_5 are products of small numbers (of the unit interval) and therefore could be hard to distinguish from zero empirically even if their true value is non-zero.

Nevertheless, the overall impact of the inflation polynomial should be directly reflected in the a_2 parameter, and given an estimate of the linearized equation (6) we can test the other interesting hypotheses as follows:

1. First, $c_3 = 0$ (irrelevance of past inflation for indexed prices) can be tested by considering $a_3 = 0$ (provided that $c_2 \neq 0$).

2. Next, the test of $c_\pi = \bar{\pi}$ (the constant indexation rate equals average inflation) amounts to a test of the hypothesis $-a_4/(2a_2 + a_3) = \bar{\pi}$ (again with the delta method).

3. And finally, the related hypothesis $c_\pi = 0$ (no constant indexation term, as a one-sided test) can simply be tested as $a_4 = 0$, which is linked to $c_\pi = 0$ via the condition $c_4 = 0$. Alternatively we could again use the delta method and test $-a_4/(2a_2 + a_3) = 0$.

The decomposition of the impact of inflation moments on average RPV can of course also be calculated within the linearized parametrization, which yields:

$$
\begin{aligned}
(1-a_1)\mathsf{E}(rpv) \quad = \quad & a_0 + (a_2 + a_5)\mathsf{Var}(\pi) \\
& + (a_2 + a_3 + a_5)\mathsf{E}^2(\pi) + (a_4 + a_6)\mathsf{E}(\pi) \\
& + a_3 \mathsf{AutoCov}(\pi, \pi_{-1})
\end{aligned}
\tag{7}
$$

As before, the possible relevance of past inflation for indexation (i.e. $a_3 \neq 0$) would directly imply that the persistence (autocovariance) of inflation affects average RPV levels.

2.2 Estimators

Apart from OLS which is used for comparison purposes or whenever the endogeneity problem is not relevant, we employ standard instrumental-variable estimators (IV) or generalized method-of-moments approaches (GMM). The test for endogeneity bias is the standard Hausman test. However, since the three regressors $\pi_t, \pi_t \pi_{t-1}, \pi_t^2$ are all functions of a single endogenous variable, it is not entirely clear whether the appropriate degrees of freedom for this test are really three. To be on the safe side here we could also evaluate the test statistic under the χ^2 distribution with only two degrees of freedom, such that the test with three degrees of freedom will be conservative. As a check of the validity of the instruments we use the standard Sargan test whenever possible.

For the GMM estimator we use a two-step variant with an initial weighting matrix based on $(Z'Z)^{-1}$, where Z is the matrix of instruments. For the linearized variants this essentially means that a consistent estimate of the weighting matrix is formed based on first-step IV estimates. This estimated weighting matrix is then used to calculate the second-step GMM estimates. Since the two-step GMM estimator is already asymptotically efficient, the J test for validity of the overidentifying orthogonality conditions is available.

All computations and estimations were performed with gretl 1.8 (Cottrell and Lucchetti, 2009).

3 Data

(For details see the data appendix.) We use monthly sectoral sub-indices along with appropriate weights series from the PPI and the CPI to calculate the time series of the cross-sectional variances as our measures of RPV.[11] Our CPI-based time series only start in 1999 because the CPI composition changed in 1998, but the PPI analysis covers a longer time span. Apart from this exogenously given data availability, we consider the PPI data to be more relevant for analyzing domestic price setting behavior because the CPI partially reflects import prices and indirect taxes.

[11] Silver and Ioannidis (2001) argue that using the coefficient of variation instead of the variance or standard deviation is advisable because uniform growth of all disaggregate variables induces a spurious increase of the cross-sectional variance (due to the scale dependence of the variance). However, this argument does not hold for variables in logarithms, but only holds for "raw" variables. While they treat the sectoral inflation rates as the "raw" variables from which the cross-sectional variance is computed, we follow economic theory by regarding the sectoral price index *levels* as the relevant "raw" input and take logarithms. Then we apply the typical next step of the RPV literature and filter out idiosyncratic long-run trends of the sectoral log prices with the first-difference filter, but that still means that the sectoral components have been log-transformed.

Since we use 100 PPI sub-groups, figure 1 only depicts the 15 largest PPI sub-aggregates that together cover 55 per cent of the aggregate PPI. The time series of all CPI sub-indices are shown in figure 2. The visual impression strongly confirms the need to filter out the idiosyncratic sectoral trends prior to the calculation of the cross-sectional variance, otherwise this variance series would be clearly trending upwards. Of course, in the existing RPV literature as well as in this paper this is achieved by taking first differences of the sub-indices and thus by actually looking at relative inflation variability.[12] Thus we constructed the relative inflation variability by using the formula

$$rpv_t^n = \sum_i w_i(\Delta log(p_{i,t}) - \Delta log(\bar{p}_t))^2,$$

where $p_{i,t}$ is the price index of the i-th PPI (or CPI) sub-group, $\bar{p}_t$ denotes aggregate PPI (CPI) and w_i is the weight of the i-th sub-group in the aggregate price index. Finally this RPV measure is standardized to have a mean of zero and unit variance, $rpv = (rpv_t^n - \overline{rpv_t^n})/\sqrt{\mathsf{V}(rpv_t^n)}$.

The inflation and RPV time series for both datasets are shown in figures 3 and 4. Given that inflation is squared in our equation, it is especially important to remove the most apparent outliers of the inflation series. For the extraordinary price hike especially in fuels and private transportation due to hurricane Katrina in 2005m9 we therefore include an additive impulse dummy as a regressor and instrument in all equations.

Since we are working with a dynamic framework it seems worthwhile to consider some descriptive statistics concerning the dynamic properties of the individual time series.

[12] Even after filtering out the (deterministic as well as stochastic) trends from the sectoral sub-indices, one may wonder how it is possible to calculate a meaningful measure of cross-sectional dispersion given that the levels of each of these sub-indices is arbitrary. Indeed, if $log(p_{i,t})$ is the price index of sector i, the sample mean of $\Delta log(p_{i,t})$ describes the time-average but sector-specific price trend. These sector-specific long-run characteristics should also be filtered out for business-cycle analysis because they describe long-run intersectoral equilibria, and for RPV studies we are interested in deviations from this equilibrium. Thus in principle the sectoral inflation rates should be demeaned before calculating the cross-sectional variance, something that has never been done in the RPV literature to our knowledge. However, for our datasets it turned out that the additional de-meaning did only make a negligible difference, and thus we followed the existing literature and did *not* perform the de-meaning, either.

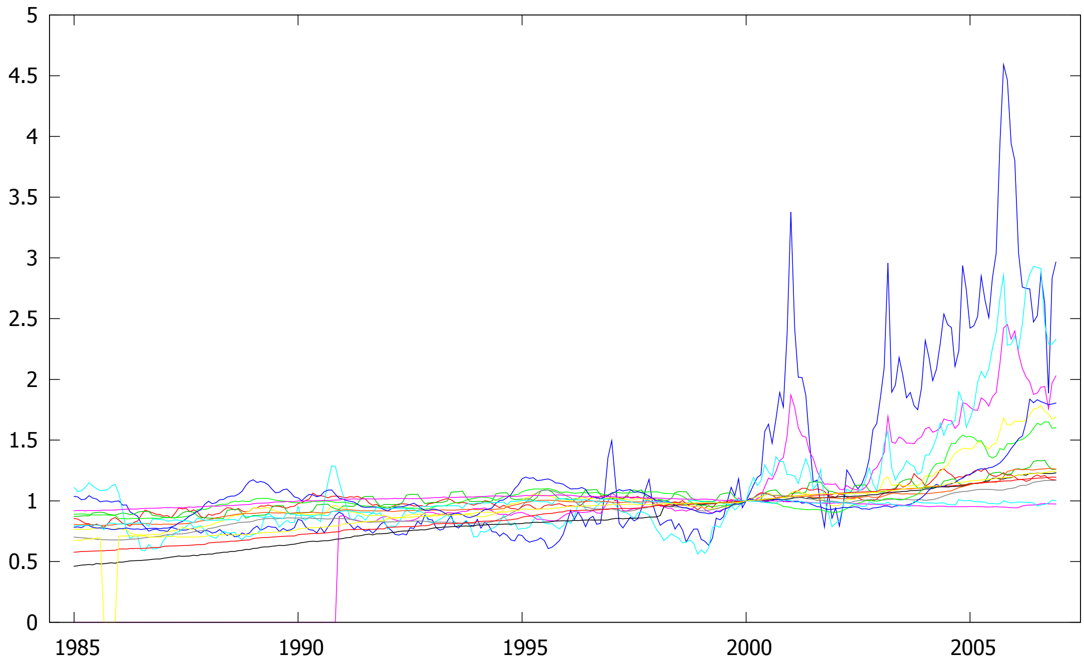

Figure 1: PPI subindices. To avoid clutter only the indices of the 15 most important categories are shown. Raw index values, rebased to the common base period 2000m1.

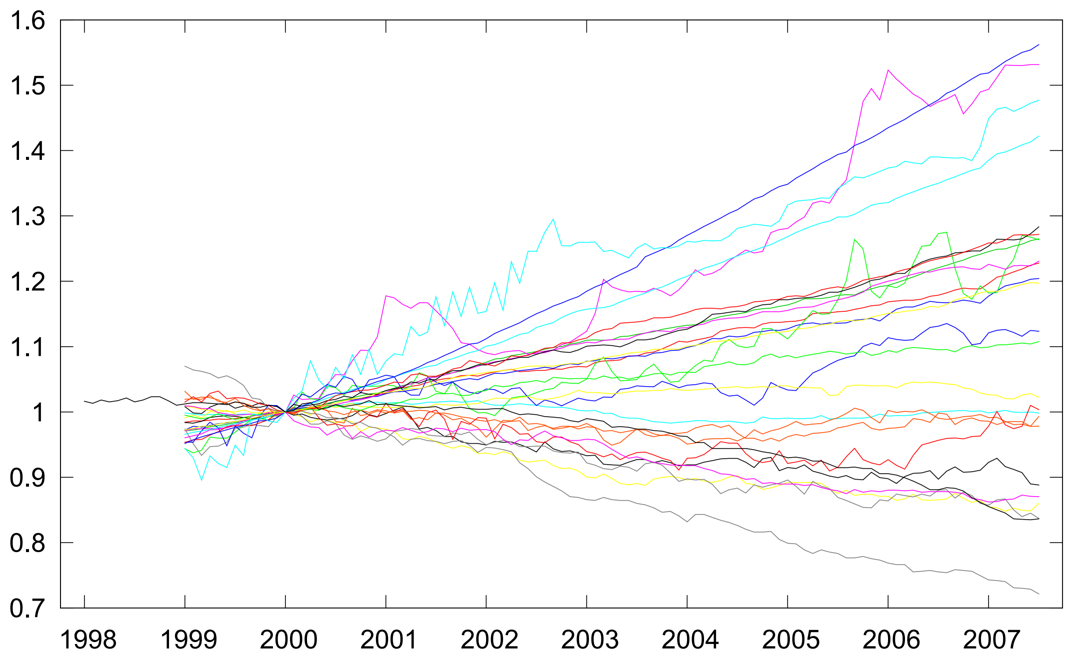

Figure 2: CPI subindices. Raw index values, rebased to the common base period 2000m1.

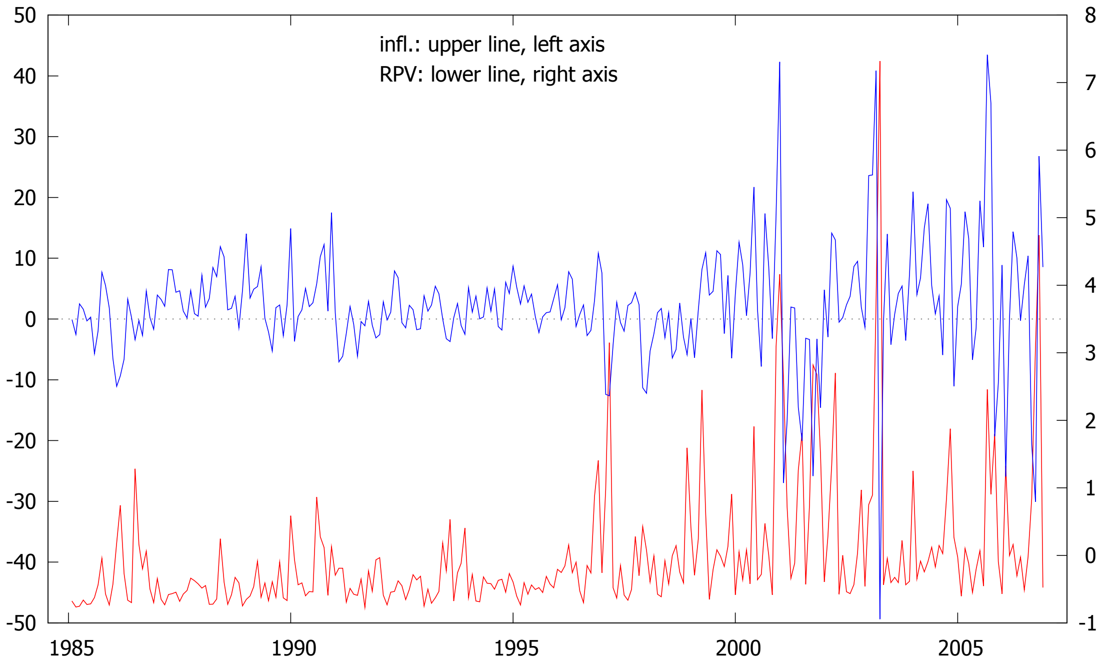

Figure 3: PPI inflation and (standardized) RPV data

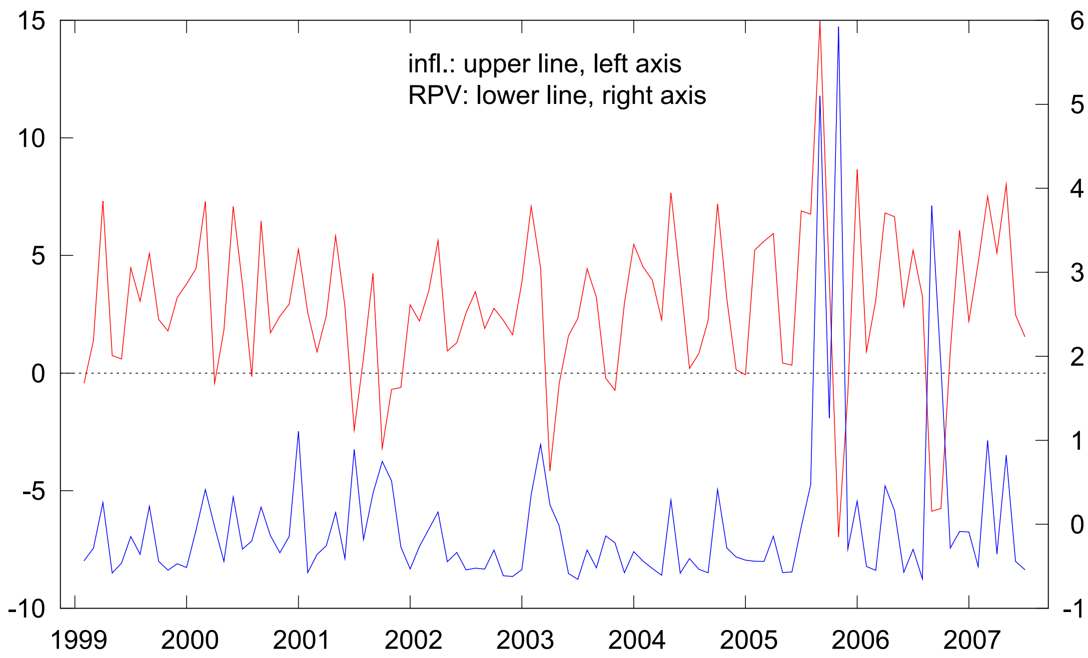

Figure 4: CPI inflation and (standardized) RPV data.

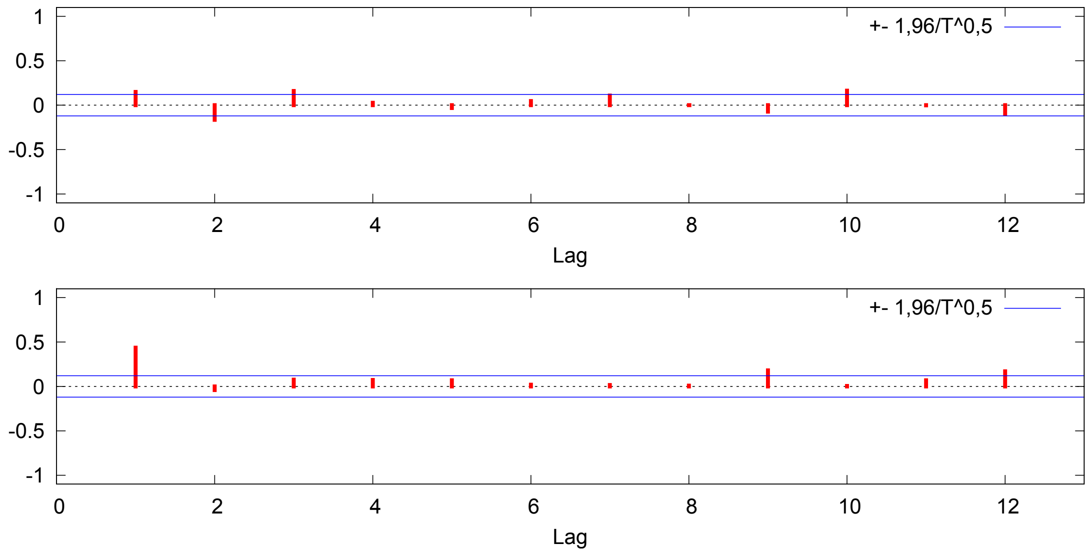

Figure 5: Dynamic characteristics of PPI inflation and RPV. Partial auto-correlation coefficients, upper panel inflation, lower panel RPV.

Figures 5 and 6 show the (partial) autocorrelation functions of inflation and RPV in both datasets. It can be seen that the PPI RPV contains first-order serial correlation, whereas the CPI RPV series is close to being white noise. But one issue here is the smaller sample of the CPI data which renders the uncertainty around the autocorrelation estimates fairly large. For PPI inflation the positive first-order autocorrelation is also obvious, but for CPI inflation in this fairly short sample of monthly data not much persistence is apparent.

4 Empirical results

4.1 Chosen instruments

Given that in the macroeconomy all contemporaneous variables are potentially endogenous we limit ourselves to lagged values of the variables described below, but finding appropriate instruments generally remains a difficult problem. We tackle this issue by implementing the following algorithm:

1. Apart from own lags of the potentially endogenous variables (π_t, π_t^2, $\pi_t \pi_{t-1}$) and

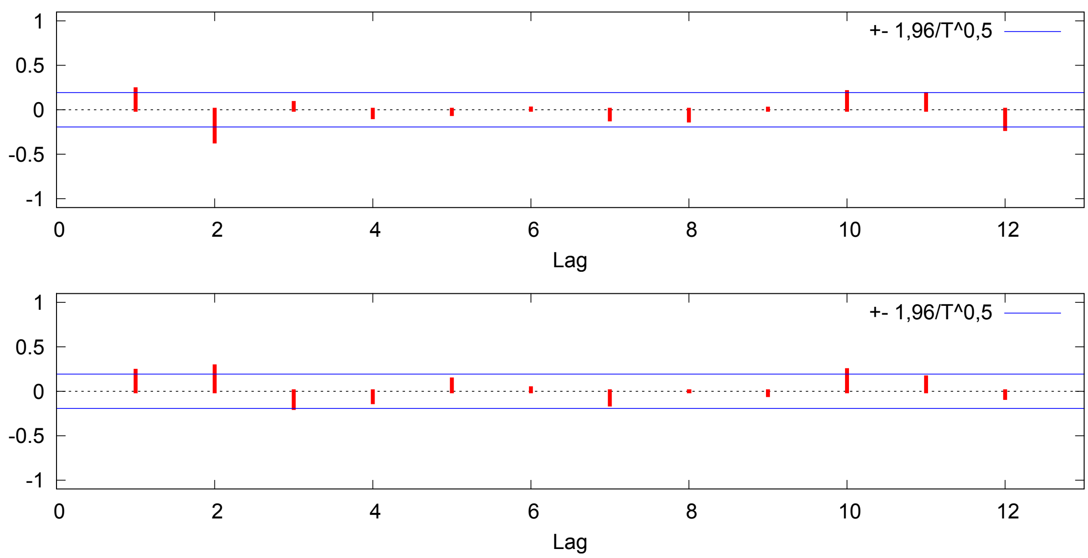

Figure 6: Dynamic characteristics of CPI inflation and RPV. Partial auto-correlation coefficients, upper panel inflation, lower panel RPV.

of RPV we include (lags of) the following variables as potential instruments: the federal funds rate, the 3-month treasury bill rate, the unemployment rate, and a (log-differenced) industrial production index. Because of the nonlinear transformation of inflation we also consider (lags of) squares (x_t^2) and intertemporal cross products ($x_t x_{t-1}$) of all those variables.

2. For each of the three variables (π_t, π_t^2, $\pi_t \pi_{t-1}$) we set up a linear regression with the entire set of potential instruments as explanatory variables.

3. For each of these auxiliary equations we perform an exhaustive general-to-specific reduction which is automated by PcGets (Hendry and Krolzig, 2001). The Gets method starts with the general model and removes redundant regressors successively.

4. The set of chosen instruments is given by the union of the regressors selected by Gets in the three auxiliary equations.[13]

[13]For the traditional bivariate specification, which is reported below for comparison purposes, we only include the regressors selected in the π_t^2-equation because π_t and $\pi_t \pi_{t-1}$ do not enter in the bivariate equa-

Table 1: Selected instruments

specification	instruments
CPI bivariate	$\pi_{t-1}\pi_{t-2}$, tbr_{t-2}
PPI bivariate	π^2_{t-1}, $\pi_{t-1}\pi_{t-2}$
CPI	π_{t-2}, $\pi_{t-1}\pi_{t-2}$, ffr_{t-2}, tbr_{t-1}, tbr_{t-2}, $rpv_{t-1}rpv_{t-2}$
PPI	π_{t-2}, $\pi_{t-1}\pi_{t-2}$, rpv^2_{t-2}, $rpv_{t-1}rpv_{t-2}$, $rpv_{t-2}rpv_{t-3}$, ip^2_{t-1}, ffr_{t-1}, ffr_{t-2}

Notes: federal funds rate (ffr), 3-month treasury bill rate (tbr), unemployment rate (u), (log-differenced) industrial production (ip). "Bivariate" refers to (1).

The instruments selected by this algorithm for each PPI and CPI specification are listed in table 1.

4.2 Estimates

The estimates of our various specifications and datasets are reported in tables 2 through 4.[14] All equations include a dummy for the effects of hurricane Katrina, except where explicitly stated otherwise.

All specifications show the expected positive impact of squared inflation which reflects the positive sign of c_2 in the theoretical equation. A somewhat surprising result is given by the relatively low values of the c_1 or a_1 coefficients relating to lagged RPV; for the CPI estimates it is even negative or insignificant. The Hausman test indicates that there is an endogeneity problem with respect to inflation for both datasets and thus the standard OLS approach suffers from the corresponding endogeneity bias. In contrast, it is reassuring that the Sargan and J over-identification tests confirm the validity of the used instruments or moment conditions. The diagnostic tests indicate that the residuals of all specifications are free from autocorrelation and ARCH effects; in any case we use robust

tion. Here it sometimes turned out that it was only possible to satisfy the Sargan tests for instrument validity if some of the originally selected instruments were removed for that specification.

[14]For comparison purposes the next subsection includes the results of the traditional bivariate-static approach.

estimates for the covariance matrices.

The direct estimation of the nonlinear equation (3) with the PPI data is displayed in table 2. Whether or not the Katrina dummy is included does not change the qualitative results, which indicate that the coefficient of past inflation is nearly zero and statistically insignificant, but that the constant indexation term is plausible and significant. As discussed before, this means that (some of the) non-optimized prices are raised according to an indexation rule which does not refer to aggregate inflation of the last period, but instead using the same rate over time.

The irrelevance of past aggregate inflation for indexation is also found in the linearized version of the equation when estimated with the PPI data, see table 5 for a comparison of all specifications. This also means that we find no evidence that higher persistence (first-order autocovariance) of inflation would decrease average RPV levels. However, in that table we also see that the estimates with the CPI data imply a different conclusion; there past inflation seems relevant and the implied value for c_3 is $\hat{a}_3/(-2\hat{a}_2) = 0.33$ (using the linearized GMM estimates from table 4), which is also plausible. Thus it appears to be important which price data is used to analyze price dispersion. Given the tax and foreign trade content of the CPI we regard the PPI data as better suited to tackle RPV issues.

In table 6 we have assembled the tests and estimates relating to the (implicit) constant term c_π of the indexation rule. We already saw in table 2 that the direct nonlinear estimates indicate the importance of this term, given the significance of the c_4 estimate. The results in table 6 show that this finding is confirmed by the CPI variants but not by the linearized specifications with the PPI data. This discrepancy between the nonlinear and linearized PPI estimates is somewhat unfortunate but the linearized PPI estimates are actually not very informative at all with respect to the constant indexation term; the test of the hypothesis that this indexation term equals the observed average inflation rate in the last column of table 6 cannot be rejected either in the linearized PPI variant. More importantly, however, this is a uniform result of all specifications and therefore our results

Table 2: Nonlinear GMM estimates (PPI data)
$rpv_t = c_0 + c_1 rpv_{t-1} + c_2(\pi_t - c_3\pi_{t-1} - c_4)^2 + u_t$

	w/o dummies	w/ Katrina dummy
c_0	-0.31^{**} 0.044	-0.31^{**} 0.042
c_1	0.12^{*} 0.052	0.11^{*} 0.050
$c_2 \times 100$	0.28^{**} 0.030	0.28^{**} 0.029
c_3	-0.052 0.0709	-0.038 0.0629
c_4	3.36^{*} 1.583	4.54^{**} 1.569
J over-id test	9.19 [.24]	10.5 [.16]
R^2	.62	.63

Notes: π is annualized monthly inflation. HAC-robust standard errors below estimates, p-values in brackets. R^2 defined as squared correlation between actual and fitted. * – 5%, ** – 1% significance level (one-sided t-test for c_1, c_2, c_4)

are compatible with the assumption that prices are indexed to what is sometimes called "trend inflation".

4.3 Memo item: traditional bivariate specifications

For purposes of comparison we also report estimates of traditional bivariate specifications in table 7, although we know from our main results that the traditional specifications will suffer from omitted variable bias. Not surprisingly we still find a positive effect of (squared) inflation on RPV. However, we detect significant error autocorrelation, and for the CPI dataset we find that the Hausman test rejects the OLS estimates due to endogeneity problems, as well as a considerably worse fit. Therefore we reach the clear verdict that the traditional specification is not an adequate model of the RPV-inflation relation.

Table 3: Linearized estimates for the PPI data

$$rpv_t = a_0 + a_1 rpv_{t-1} + a_2 \pi_t^2 + a_3 \pi_t \pi_{t-1} + a_4 \pi_t + a_5 \pi_{t-1}^2 + a_6 \pi_{t-1} + \varepsilon_t$$

	memo: OLS	IV	GMM
const (a_0)	-0.20^{**} 0.043	-0.25^{**} 0.047	-0.28^{**} 0.038
rpv_{t-1} (a_1)	0.22^{**} 0.060	0.18^{*} 0.078	0.19^{**} 0.069
π_t^2 ($a_2 \times 100$)	0.31^{**} 0.020	0.43^{**} 0.073	0.43^{**} 0.060
$\pi_t \pi_{t-1}$ ($a_3 \times 100$)	-0.061 0.0332	-0.080 0.0643	-0.071 0.0640
π_t ($a_4 \times 100$)	-0.55 0.645	-0.51 1.448	-0.28 1.163
π_{t-1}^2 ($a_5 \times 100$)	-0.055^{*} 0.0260	-0.098^{**} 0.0338	-0.096^{**} 0.0305
π_{t-1} ($a_6 \times 100$)	-1.1 0.71	-2.0^{**} 0.69	-1.7^{**} 0.55
Sargan/J over-id test	n.a.	3.91 [.56]	4.29 [.51]
Hausman	11.70 [.008]		n.a.
no AC(6)	1.77 [.11]	0.69 [.66]	n.a.
no ARCH(2)	1.24 [.54]	2.48 [.29]	n.a.
R^2	.68	.67	.67

Notes: π is annualized monthly inflation. HAC-robust standard errors below estimates, p-values in brackets. R^2 defined as squared correlation between actual and fitted. Sargan over-identification test for IV-estimation, J-test for GMM-estimation.
* – 5%, ** – 1% significance level (one-sided t-test for a_1, a_2)

Table 4: Linearized estimates for the CPI data

$rpv_t = a_0 + a_1 rpv_{t-1} + a_2\pi_t^2 + a_3\pi_t\pi_{t-1} + a_4\pi_t + a_5\pi_{t-1}^2 + a_6\pi_{t-1} + \varepsilon_t$

	memo: OLS	IV	GMM
c (a_0)	-0.276^{**} 0.066	-0.171 0.106	-0.165 0.096
rpv_{t-1} (a_1)	-0.054 0.119	-0.051 0.195	0.011 0.188
π_t^2 (a_2)	0.050^{**} 0.006	0.043^{**} 0.016	0.052^{**} 0.013
$\pi_t\pi_{t-1}$ (a_3)	-0.004 0.009	-0.044^{*} 0.021	-0.034^{**} 0.010
π_t (a_4)	-0.261^{**} 0.039	-0.212^{*} 0.108	-0.277^{**} 0.081
π_{t-1}^2 (a_5)	0.007 0.006	0.016^{*} 0.009	0.0095 0.0084
π_{t-1} (a_6)	0.011 0.044	0.044 0.054	0.057 0.047
Hausman no-endog. test	21.32 [0.00]		n.a.
Sargan/J over-id test	n.a.	4.25 [0.24]	3.16 [0.37]
AC(6) test	0.19 [0.98]	0.64 [0.70]	n.a.
ARCH(2) test	2.77 [0.25]	4.24 [0.12]	n.a.
R^2	0.82	0.66	0.75

Notes: π is annualized monthly inflation. HAC-robust standard errors below estimates, p-values in brackets. R^2 defined as squared correlation between actual and fitted. Sargan over-identification test for IV-estimation, J-test for GMM-estimation.
* – 5%, ** – 1% significance level (one-sided t-test for a_1, a_2)

Table 5: Test for relevance of past inflation for indexation

Specification	test statistic	p-value
PPI		
memo: linearized OLS	-1.83	.068
linearized IV	-1.24	.22
linearized GMM	-1.10	.27
nonlinear GMM	-0.60	.55
CPI		
memo: linearized OLS	-0.44	.66
linearized IV	-2.13	.034
linearized GMM	-3.23	.001

Notes: Tests based on the parameters c_3 and a_3, two-sided. If these are non-zero, this also implies that the autocovariance of inflation affects average RPV levels, see the text.

Table 6: Tests and estimates relating to the constant term for indexation

Specification	estimated c_π	test of $c_\pi = 0$ (based on c_4 or a_4)	test of $c_\pi = 0$ (delta method)	test of $c_\pi = \bar{\pi}$
PPI				
memo: linearized OLS	0.99	0.86 [.20]	0.88 [.19]	-1.14 [.25]
linearized IV	0.66	0.35 [.36]	0.36 [.36]	-0.89 [.37]
linearized GMM	0.36	0.24 [.40]	0.25 [.40]	1.33 [.18]
nonlinear GMM	4.37	2.89 [.002]	3.07 [.001]	1.47 [.14]
CPI				
memo: linearized OLS	2.73	6.74 [0]	14.15 [0]	-0.72 [.47]
linearized IV	4.95	1.97 [.025]	1.74 [.041]	0.74 [.46]
linearized GMM	3.92	3.41 [.001]	4.02 [0]	1.08 [.28]

Notes: P-values in brackets. The parameter c_π describes the constant indexation component of non-optimized prices, for details see the text. Observed mean inflation is given by $\bar{\pi}$. The tests for $c_\pi = 0$ are one-sided.

Table 7: Bivariate estimates

$rpv_t = b_0 + b_2\pi_t^2 + u_t$

	CPI-OLS	CPI-IV	CPI-IV w/o Katrina dummy	PPI-OLS	PPI-IV
c (b_0)	-0.423^{**} 0.056	-1.293 0.694	-1.202^{**} 0.461	-0.30^{**} 0.047	-0.30^{**} 0.060
π_t^2 (b_2)	0.022^{**} 0.005	0.073 0.042	0.063^{*} 0.025	0.0030^{**} 0.00024	0.0031^{**} 0.001
Hausman no-endog. test	3.54 [.06]		10.16 [0]	0.24 [.63]	
Sargan over-id. test	n.a.	2.34 [.13]	0.02 [.88]	n.a.	0.74 [.39]
AC(6) test	1.92 [.09]	0.48 [.82]	2.51 [.03]	4.56 [0]	3.99 [.001]
ARCH(2) test	0.30 [.86]	4.47 [.11]	7.74 [.02]	1.64 [.44]	1.55 [.46]
R^2	0.41	0.30	0.42	0.61	0.61

Notes: π is annualized monthly inflation. Robust standard errors below estimates, p-values in brackets. R^2 defined as squared correlation between actual and fitted. In the CPI-IV variant the Katrina dummy is actually redundant but affected the test results, hence we also present the specification without it.

* – 5%, ** – 1% significance level

5 Conclusions

In this paper we have revisited the single-equation approach to measuring the impact of inflation on price dispersion (RPV). Employing a non-linear functional form derived from economic theory with some generalizations, our approach reflects the possibility that some price setters may partially index their own prices to past inflation rates and/or raise them by a constant rate in each period. We also took special care of the potential endogeneity of inflation, which is usually ignored in the RPV literature. Analyzing two datasets with sectoral sub-aggregates of the PPI and the CPI in the USA we found that the endogeneity bias as well as the extensions are empirically relevant, which casts some doubts on many estimates in the literature.

In some sense, our results are nevertheless still in accordance with many earlier findings, as they also show that inflation fluctuations increase RPV. This effect is the main channel of modern theoretical monetary models through which inflation reduces welfare, and therefore our results support this assumption. But in our generalized specification we found that average ("trend") inflation is taken into account by price setters in their indexation rule, and therefore historical average inflation rates are the relevant benchmark to measure inflation deviations. Another finding is that yesterday's inflation rates seem less important for price indexation. This means that our results do not provide strong evidence in favor of a policy of gradual instead of sudden inflation adjustments after inflation has deviated from its historical average.

When comparing our results to other results in the literature it is important to bear in mind that our results refer exclusively to expected inflation. The reason is our use of instrumental-variable techniques in conjunction with our choice of lagged variables as instruments,[15] and those can only contain information for the expected part of inflation. The flip side of this statement is that it may well be the case that earlier analyses of

[15] We confined ourselves to lagged variables as instruments because ultimately any contemporaneous macro variable is likely to be endogenous in the sense of being correlated with innovations in RPV.

unexpected inflation all suffer from endogeneity biases. However, it is also important to acknowledge that no omitted-variable bias arises in our estimates because by definition unexpected inflation is uncorrelated with expected inflation. Furthermore, assessing the cost of expected inflation appears much more important for policy makers, because that is the cost arising from systematic policy, whereas the Lucas critique teaches that effects of unexpected inflation could not be exploited by policy anyway.

With respect to future work the most pressing issue concerning the theoretical foundation of the estimated equation is related to the non-zero average levels of inflation. Here it would be desirable to have a rigorous derivation of the RPV-inflation relation with non-zero equilibrium inflation, but theoretical work has just recently begun to take the issue of trend inflation seriously. Future empirical work would naturally search for more or other valid instruments to check the robustness of the results.

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A Data appendix

A.1 PPI Data

The source for both datasets is the US Department of Labor (Bureau of Labor Statistics). The PPI data consists of the index values of 100 sub-aggregates that altogether cover the aggregate PPI, taken from the web site of the Bureau of Labor Statistics (BLS). The data is given in monthly form, starting 1985m01 and extending until 2006m12. The data is not seasonally adjusted, and the aggregate PPI was generated by weighting and summing all sub-aggregate indices. Since weight series are not available, the weights are constant over time.

The PPI sub-aggregates are as follows: 1. Fruits & melons, fresh/dry vegs. & nuts, 2. Grains, 3. Slaughter livestock, 4. Slaughter poultry, 5. Plant and animal fibers, 6. Fluid milk, 7. Chicken eggs, 8. Hay, hayseeds and oilseeds, 9. Cereal and bakery products, 10. Meats, poultry and fish, 11. Dairy products, 12. Processed fruits and vegetables, 13. Sugar and confectionery, 14. Beverages and beverage materials, 15. Fats and oils, 16. Miscellaneous processed foods, 17. Prepared animal feeds, 18. Synthetic fibers, 19. Processed yarns and threads, 20. Gray fabrics, 21. Finished fabrics, 22. Apparel & other fabricated textile products, 23. Miscellaneous textile products/services, 24. Hides and skins, incl. Cattle, 25. Leather, 26. Footwear, 27. Other leather and related products, 28. Coal, 29. Gas fuels, 30. Electric power, 31. Utility natural gas, 32. Crude petroleum (domestic production), 33. Petroleum products, refined, 34. Petroleum and coal products, n.e.c., 35. Industrial chemicals, 36. Paints and allied products, 37. Drugs and pharmaceuticals, 38. Fats and oils, inedible, 39. Agricultural chemicals and chemical products, 40. Plastic resins and materials, 41. Other chemical and allied products, 42. Rubber and rubber products, 43. Plastic products, 44. Lumber, 45. Millwork, 46. Plywood, 47. Other wood products, 48. Logs, bolts, timber and pulpwoods, 49. Prefabricated wood buildings and components, 50. Treated wood and contract wood preserving, 51. Pulp, paper and prod., ex. bldg. paper, 52. Building paper & building board mill products, 53. Publications, printed matter & printing material, 54. Iron and steel, 55. Nonferrous metals, 56. Metal containers, 57. Hardware, 58. Plumbing fixtures and fittings, 59. Heating equipment, 60. Fabricated structural metal products, 61. Miscellanous metal products, 62. Metal treatment services, 63. Agricultural machinery and equipment, 64. Construction machinery and equipment, 65. Metalworking machinery and equipment, 66. General purpose machinery and equipment, 67. Electronic computers and computer equipment, 68. Special industry machinery and equipment, 69. Electrical machinery and equipment, 70. Miscellaneous instruments, 71. Miscellaneous machinery, 72. Household furniture, 73. Commercial furniture, 74. Floor coverings, 75. Household appliances, 76. Home electronic equipment, 77. Other households, durable goods, 78. Glass, 79. Concrete ingredients and related products, 80. Concrete products, 81. Clay construction products ex. Refractories, 82. Refractories, 83. Asphalt felts and coatings, 84. Gypsum products, 85. Glass containers, 86. Other nonmetallic minerals, 87. Motor vehicles and equipment, 88. Aircraft and aircraft equipment, 89. Ships and Boats, 90. Railroad equipment, 91. Transportation equipment, n.e.c., 92. Toys, sporting goods, small arms, etc., 93. Tobacco products, incl. stemmed & redries, 94. Notions, 95. Photographic equipment and supplies, 96. Mobile homes, 97. Medical, surgical & personal aid devices, 98. Industrial safety equipment,

99. Mining services, 100. Other miscellaneous products.

A.2 CPI Data

All CPI data are US city averages for All Urban Consumers which, according to the BLS, covers approximately 87 percent of the total U.S. population. Our data consists of index values of 25 CPI sub-aggregates, altogether covering the entire aggregate CPI. We use monthly series from 1999m01 through 2007m07, seasonally adjusted at the source except for the photo category. Our sample start is determined by the 1998 revision of the CPI sub-aggregates. All series were rebased to 2000m01. We generated the aggregate CPI series by a weighted sum of all sub-aggregates. The weights time series used to generate this series are also provided by the BLS (annual frequency).

The CPI sub-aggregates after the 1998 CPI revision are as follows: 1. Food, 2. Alcoholic beverages, 3. Shelter, 4. Fuels and utilities, 5. Household furnishings and operations, 6. Men's and boys' apparel, 7. Women's and girls' apparel, 8. Footwear, 9. Infants' and toddlers' apparel, 10. Jewelry and watches, 11. Private transportation, 12. Public transportation, 13. Medical care commodities, 14. Medical care services, 15. Video and audio, 16. Pets, pet products and services, 17. Sporting goods, 18. Photography, 19. Other recreational goods, 20. Recreation services, 21. Recreational reading materials, 22. Education, 23. Communication, 24. Tobacco and smoking products, 25. Personal care.