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Sticky prices or rational inattention – What can we learn from sectoral price data?*

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Abstract

This paper derives stylised facts on sectoral inflation dynamics and confronts these facts with two popular theoretical models of price setting. Based on sectoral price responses to macroeconomic shocks estimated from an approximate factor model, we find that the frequency of price changes explains a substantial share of the cross-sectional variation of the speed and size of responses. Moreover, there is little evidence that the volatility of sectoral inflation due to idiosyncratic shocks dampens the size and speed of the responses to macroeconomic shocks. These findings support a multi-sector model with sticky prices rather than a rational inattention model. We derive the results with different modelling and sampling decisions proposed in the literature and we find that the explanatory power of the frequency of price changes for the speed of response to a macroeconomic shock proves robust to these decisions. Other results are sensitive with respect to the choice of the factor model and the treatment of outliers.

JEL classification: E31, E4, E5, C3
Keywords: heterogeneity in price setting, sectoral price data, multi-sector sticky-price model, rational inattention, approximate factor model

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1 Introduction

Recent theoretical models in monetary economics try to match the empirical evidence on the behaviour of the aggregate price level with that on firms' price-setting behaviour. In particular, advances have been made in reconciling the high persistence of aggregate inflation with the relatively frequent price adjustments observed at the micro level. By contrast, earlier models – such as the Calvo (1983) model – cannot explain the large degree of monetary non-neutrality at the macro level, at least without assuming rather high real rigidities (Mackowiak and Smets, 2008).

One way to explain the mismatch between the macro and the micro facts on prices is put forward by Boivin et al. (2009) and Mackowiak et al. (2009), BGM and MMW henceforth. They document that prices react slowly to macroeconomic shocks but quickly to idiosyncratic shocks. Two popular price-setting theories that are able to explain this finding are rational inattention and multi-sector sticky-price models. Mackowiak and Wiederholt (2009) argue that if idiosyncratic shocks are large relative to macroeconomic shocks it is rational for individual firms to direct most of their attention to the idiosyncratic shocks. As a consequence, even though prices are adjusted every period, macroeconomic shocks are incorporated only slowly into prices while idiosyncratic shocks trigger faster and larger responses. Other authors emphasise the macroeconomic implications of multiple sectors with different degrees of price stickiness (Carvalho, 2006; Nakamura and Steinsson, 2010). In these models, the slow reaction to macroeconomic shocks stems from across-sector pricing complementarity. However, the speed of response to idiosyncratic shocks in these models is too slow to match the empirical responses in BGM. Carvalho and Lee (2011) show that augmenting a model by within-sector pricing substitutability can generate responses that are quantitatively close to those presented in BGM.

The purpose of this paper is to document stylised facts on sectoral price dynamics and to confront these facts with theoretical models of rational inattention and sticky prices. It thereby adds to a growing literature using factor models to analyse the sectoral and geographic dimensions of inflation.[1] In this paper, the stylised facts are derived from an approximate factor model. This model allows us to decompose sectoral inflation rates from Switzerland's consumer price index (CPI) into an idiosyncratic and a common component. Based on this decomposition, we analyse the sectoral price responses to idiosyncratic and macroeconomic shocks. Our contribution to the literature is threefold. First, we show which results presented in BGM and MMW continue to hold on a different data set for a different country. Second, we evaluate two theoretical models of price setting in terms of their ability to match the sectoral price facts. Third, we evaluate why some of our results, which are derived based on the same methodology as BGM, differ from MMW.

Our findings may be summarised as follows. The main sectoral price facts documented in BGM and MMW continue to hold using Swiss data. While sectoral prices react only slowly to macroeconomic shocks, they react relatively quickly to idiosyncratic shocks. With aggregation, idiosyncratic shocks cancel each other out such that aggregate CPI inflation is mainly driven by macroeconomic shocks. These sectoral price facts call for theoretical models that are able to explain different responses of firms to macroeconomic and idiosyncratic shocks.

We then show that our sectoral price facts are more consistent with a multi-sector sticky-price model than with a rational inattention model. To this end, we regress the size and speed of the responses to a macroeconomic shock on sectoral descriptive statistics. There is little evidence that the size and speed of price responses to macroeconomic shocks are lower in sectors with a volatile idiosyncratic component. This result holds even if we control for the volatility of the common component. However, the size and speed of responses to macroeconomic shocks can to some extent be explained by differences in the frequency of price changes. The findings are consistent with multi-sector sticky-price models, where macroeconomic shocks are incorporated more quickly in sectors with more frequent price adjustments.

Our empirical strategy closely follows BGM and we mostly find evidence supporting sticky-price models. However, MMW is another influential piece of the literature using a different factor model and their results are in line with rational inattention. In the last part

[1] See e.g. Boivin et al. (2009); Mackowiak et al. (2009); Mumtaz et al. (2009); Ciccarelli and Mojon (2010); De Graeve and Walentin (2011); Beck et al. (2011); Förster and Tillmann (2013).

of the paper, we therefore shed light on why our results differ from MMW's results. We attribute the differences partly to the fact that MMW exclude outliers. However, it remains an open question, whether outliers as defined by MMW reflect large measurement errors, that should be excluded from the analysis, or whether they mirror firms' actual price-setting decisions. The remaining differences can be attributed to the fact that MMW use a different factor model. In the end, it is difficult to favour one factor model over the other. A robust finding with both approaches is that the frequency of price changes explains a substantial share of the sectoral differences in the speed of the responses to macroeconomic shocks.

We proceed by presenting the data and the factor model in Section 2. Section 3 discusses our results and Section 4 concludes.

2 Methodology and data

We use an approximate factor model to analyse sectoral inflation dynamics. The factor model allows us to decompose sectoral inflation rates into a common and an idiosyncratic component. These components can then be used to assess the reaction of sectoral inflation to macroeconomic and idiosyncratic shocks. We derive these impulse responses in a second step by estimating time-series processes for each sectoral common and idiosyncratic component. In what follows, we discuss the methodology and data set in detail.

Assume that the Swiss economy can be summarised by a $K \times 1$ vector $\mathbf{C}_t$ of static factors. These factors may reflect general economic conditions such as real economic activity or the general rate of inflation.[2] Since we do not observe $\mathbf{C}_t$ we extract it from a large data set of economic time series denoted by a vector $\mathbf{X}_t$. The number of these time series is denoted by N, which should be large relative to K and the number of time periods T. Before extracting the factors, we standardise the data so that all series are of mean zero and standard deviation

[2] In an earlier version of the paper, we estimated a FAVAR along the lines of BGM and derived the responses to an identified monetary policy shock (see Kaufmann and Lein, 2011). We decided to focus on impulse responses to an unidentified shock to the common and idiosyncratic components to make the results more comparable to MMW.

one. Let the standardised time series, $\tilde{\mathbf{X}}_t$, be related to the common factors according to

$$\tilde{\mathbf{X}}_t = \mathbf{\Lambda}\mathbf{C}_t + \mathbf{e}_t \quad , \tag{1}$$

where $\mathbf{\Lambda}$ is a $N \times K$ matrix of factor loadings. The principal component estimation which is applied to extract the common factors allows for some cross-correlation in the error term $\mathbf{e}_t$ that vanishes as N approaches infinity (see Stock and Watson, 2002b). Once the factors have been extracted, the factor loadings can be estimated by OLS.

The data set $\mathbf{X}_t$ consists of a panel of quarterly time series from Q1 1978 to Q3 2008.[3] The data include 137 macroeconomic time series, one of them is the aggregate CPI, and 147 sectoral price indices underlying the CPI. The macroeconomic data cover many aspects of the Swiss economy such as real activity, the labour market, housing and finance. In addition, we include business and consumer tendency surveys on real activity, consumer sentiment, price expectations and related matters. The price data are based on price indices at the lowest available level of disaggregation obtained from the Swiss Federal Statistical Office.[4] We refer to the growth rates of these indices as sectoral inflation rates. We aggregate some of the price indices to a higher level in order to obtain a consistent data set over the whole sample period. In addition, we have to exclude some of the price indices altogether, due to data availability restrictions. The remaining data cover 95% of the CPI at average expenditure weights.

To determine the number of static factors K, we apply the test suggested in Bai and Ng (2002). The criterion is minimised at $K = 3$ and thus we end up with three common factors. These common factors explain on average 33% of the variation in $\tilde{\mathbf{X}}_t$. At first sight, this figure seems low compared to other factor models. For example, Giannone et al. (2005) report that two factors explain more than 60% of the total variance of 200 US macroeconomic time series.

[3]If necessary, the time series are transformed to obtain stationarity, usually using the first difference of the logarithm. A full list of the data and a detailed description of the transformations are available upon request.

[4]Although the Swiss CPI is published on a monthly basis, not all prices are actually collected every month. If no survey takes place the Swiss Federal Statistical Office uses the index value of the last survey to calculate the CPI. This hampers transformations such as taking log-differences, seasonal adjustment and aggregation to quarterly frequency. We therefore use an interpolation method based on the Kalman filter to obtain an estimate of the unobserved monthly price series before they are seasonally adjusted and aggregated to quarterly frequency. See Huwiler and Kaufmann (2013) for a more detailed description of the interpolation method and the price data.

This discrepancy is partly because we add to a data set of macroeconomic time series a large panel of sectoral price data. The relatively low share explained by our factors mirrors that the variance of sectoral price series is mainly due to idiosyncratic shocks.[5] We will discuss and interpret this observation in the following section.[6]

After estimating the common factors we use equation (1) to disentangle the idiosyncratic from macroeconomic fluctuations for each sectoral inflation rate included in $\tilde{\mathbf{X}}_t$. This decomposition is of the form

$$\tilde{\pi}_{it} = \boldsymbol{\lambda}_i \mathbf{C}_t + e_{it} \quad , \tag{2}$$

where $\tilde{\pi}_{it}$ denotes the standardised quarterly log-change of the price index in sector i at time t, $\boldsymbol{\lambda}_i$ is the row vector of factor loadings for item i, and e_{it} is the sector-specific error term, which captures idiosyncratic inflation dynamics that are not attributed to dynamics of the common factors. Henceforth, we label $\boldsymbol{\lambda}_i \mathbf{C}_t$ as the common component and e_{it} as the idiosyncratic component of sectoral inflation. Equation (2) shows that the common and idiosyncratic components are derived in terms of the standardised sectoral inflation rates. In what follows, we work with the non-standardised sectoral inflation rates. That is, all further calculations are based on the idiosyncratic and common components multiplied by the standard deviation of the corresponding sectoral inflation rate.[7]

In a second step, we estimate the dynamics of π_{it}, $\boldsymbol{\lambda}_i \mathbf{C}_t$ and e_{it}. Following BGM we fit an autoregressive process with L lags of the form $y_{it} = \Sigma_{\ell=1}^{L} \rho_{i\ell} y_{i,t-\ell} + \varepsilon_{it}$, where L is the optimal number of lags chosen by the Akaike information criterion and y_{it} denotes the corresponding time series (π_{it}, $\boldsymbol{\lambda}_i \mathbf{C}_t$, or e_{it}). From these estimates, we derive impulse responses to a shock to the common component and to the idiosyncratic component. As a measure of persistence we calculate the sum of all coefficients of the $AR(L)$ process $\rho(y_{it}) = \Sigma_{\ell=1}^{L} \rho_{i\ell}$.

[5]Similarly, for the data set used by BGM, we find that five factors explain only 20% of the total variation. Excluding the disaggregate data on prices and quantities, five factors explain 54% of the total variation in the remaining data set.

[6]Note that the fraction explained by our factors is higher for key macroeconomic variables (CPI: 52%, 3M Libor: 80%, GDP: 60%).

[7]MMW use standardised impulse responses in their analysis. However, their measure of the speed of the response is not affected by the standardisation.

Table 1: *Descriptive statistics*

	(1) sd(π_{it})	(2) sd($\boldsymbol{\lambda}_i \mathbf{C}_t$)	(3) sd(e_{it})	(4) R^2	(5) $\rho(\pi_{it})$	(6) $\rho(\boldsymbol{\lambda}_i \mathbf{C}_t)$	(7) $\rho(e_{it})$
Aggregate inflation							
	0.54	0.39	0.38	0.52	0.79	0.92	0.18
Sectoral inflation							
Average	1.18	0.53	1.03	0.31	0.53	0.85	0.18
Median	0.87	0.47	0.70	0.30	0.57	0.89	0.24

Notes: The table shows statistics for aggregate CPI inflation in the first panel, as well as average and median statistics for sectoral CPI inflation in the second panel. We report the standard deviation (sd) and persistence (ρ) of inflation (π_{it}), the common component ($\boldsymbol{\lambda}_i \mathbf{C}_t$), and the idiosyncratic component (e_{it}). The standard deviation is measured in percent, the persistence is measured by the sum of autoregressive coefficients. The R^2 gives the share of variation in π_{it} explained by $\boldsymbol{\lambda}_i \mathbf{C}_t$.

3 Results

The results are presented in the following order. Section 3.1 provides descriptive statistics for the common and idiosyncratic components of sectoral inflation and the impulse responses of sectoral prices to idiosyncratic and macroeconomic shocks. Section 3.2 explains the cross-sectional differences of the size and speed of these responses in terms of time-series properties of the idiosyncratic and common components and in terms of statistics on individual price-setting behaviour. Finally, Section 3.3 discusses the robustness of the results and compares the approach used in this paper to the approach used by MMW.

3.1 Descriptive analysis

Table 1 shows that the standard deviation of aggregate inflation amounts to 0.54 (column 1). However, the average standard deviation of sectoral inflation is much higher at 1.18. Similarly, column 5 shows that the persistence of aggregate inflation (0.79) is higher than average persistence of sectoral inflation (0.53). This finding is in line with many studies that show that the aggregation process can explain a large amount of inflation persistence (see Altissimo et al., 2009, for the euro area and Elmer and Maag, 2009, for Switzerland).

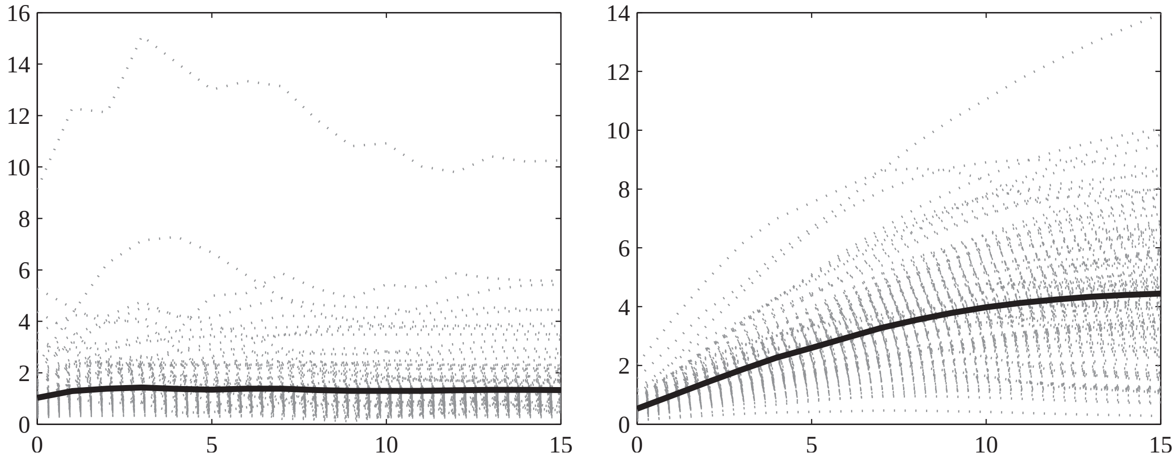
The diverging time-series properties of aggregate and sectoral inflation are in line with the idea that the idiosyncratic component is typically volatile but the common component is persistent. For sectoral inflation, the average volatility of the idiosyncratic components

(1.03) is higher than the average volatility of the common components (0.53). Similarly, the sectoral idiosyncratic components are not very persistent, while the sectoral common components are. With aggregation, idiosyncratic factors tend to cancel each other out. Thus, aggregate inflation is less volatile and more persistent than sectoral inflation. In other words, aggregate inflation can be mainly explained by macroeconomic shocks. Indeed, a large share of aggregate inflation is explained by the three common factors ($R^2 = 0.52$). By contrast, the common components explain on average only 31% of the variation in sectoral inflation. The results suggest that idiosyncratic shocks are more important than macroeconomic shocks for explaining sectoral inflation. The low average R^2 for sectoral inflation indicates that only a small fraction of the variation in sectoral inflation rates can be explained by macroeconomic shocks. Consequently, sectoral inflation is mainly driven by price changes in response to idiosyncratic shocks. Recently, De Graeve and Walentin (2011) show evidence that these volatile and non-persistent sector-specific components are consistent with temporary price movements due to sales and measurement errors.

These statistics suggest that firms' price-setting behaviour depends on the nature of the underlying shocks. While they respond strongly and swiftly to idiosyncratic shocks, they respond weakly and sluggishly to macroeconomic shocks. Figure 1 displays impulse response functions supporting this view. In most sectors, an idiosyncratic shock is fully incorporated within two quarters (Figure 1, panel a). This is corroborated by the average response. The pattern suggests that the price changes due to idiosyncratic shocks are on average only weakly autocorrelated. Since idiosyncratic shocks do not appear to have a persistent effect on sectoral inflation, this confirms that the persistence in aggregate inflation is unlikely to be driven by idiosyncratic shocks. By contrast, prices respond slowly to macroeconomic shocks (panel b). On average, it takes about three years until they converge to their new level. We have also calculated the responses as weighted averages for various categories such as goods and services or imported and domestic products.[8] The main conclusions remain the same. The response to an idiosyncratic shock is typically fast but it takes several years for a macroeconomic shock to feed fully into prices.

[8] More figures including the sectoral responses to an identified monetary policy shock are available in Kaufmann and Lein (2011, 2012).

Figure 1: *Impulse responses of sectoral prices*



(a) Idiosyncratic shock (b) Macroeconomic shock

Notes: Estimated impulse responses of sectoral CPI prices (in percent) to (a) an idiosyncratic shock of one standard deviation, and (b) a macroeconomic shock of one standard deviation. The solid lines give the average of the sectoral responses.

So far, we showed that two stylised price facts that are well known in the literature continue to hold using Swiss price data. First, because idiosyncratic shocks tend to cancel each other out with aggregation, inflation is mostly driven by macroeconomic factors. Second, prices respond more strongly and more swiftly to idiosyncratic than to macroeconomic shocks. Two popular theories that are able to match these empirical findings are a rational inattention model and a multi-sector model with sticky prices. In both models, firms react more readily and more strongly to idiosyncratic shocks than to macroeconomic shocks, but they do so for different reasons. In a rational inattention model, firms react slowly to macroeconomic shocks because they direct most of their attention to idiosyncratic shocks (Mackowiak and Wiederholt, 2009). In a model with sticky prices, firms incorporate macroeconomic shocks as well as idiosyncratic shocks once a price change occurs (Carvalho, 2006; Nakamura and Steinsson, 2010). In these models, the slow reaction to macroeconomic shocks stems from across-sector pricing complementarity. However, the speed of response to idiosyncratic shocks in these models is too slow to match the empirical responses in BGM. Carvalho and Lee (2011) show that augmenting a model by within-sector pricing substitutability can generate responses that are quantitatively close to those presented in

Table 2: *Correlation of descriptive statistics*

Variables	(1) $sd(\pi_{it})$	(2) $sd(\boldsymbol{\lambda}_i \mathbf{C}_t)$	(3) $sd(e_{it})$	(4) $\frac{sd(e_{it})}{sd(\boldsymbol{\lambda}_i \mathbf{C}_t)}$	(5) R^2	(6) FPC_i	(7) $speed_i^{macro}$	(8) $speed_i^{idio}$
$sd(\pi_{it})$	1.00							
$sd(\boldsymbol{\lambda}_i \mathbf{C}_t)$	0.73	1.00						
$sd(e_{it})$	1.00	0.67	1.00					
$\frac{sd(e_{it})}{sd(\boldsymbol{\lambda}_i \mathbf{C}_t)}$	0.50	-0.08	0.55	1.00				
R^2	-0.49	-0.01	-0.55	-0.74	1.00			
FPC_i	0.77	0.56	0.76	0.43	-0.30	1.00		
$speed_i^{macro}$	0.38	0.28	0.39	0.33	-0.44	0.36	1.00	
$speed_i^{idio}$	0.24	0.03	0.26	0.38	-0.39	0.05	0.15	1.00

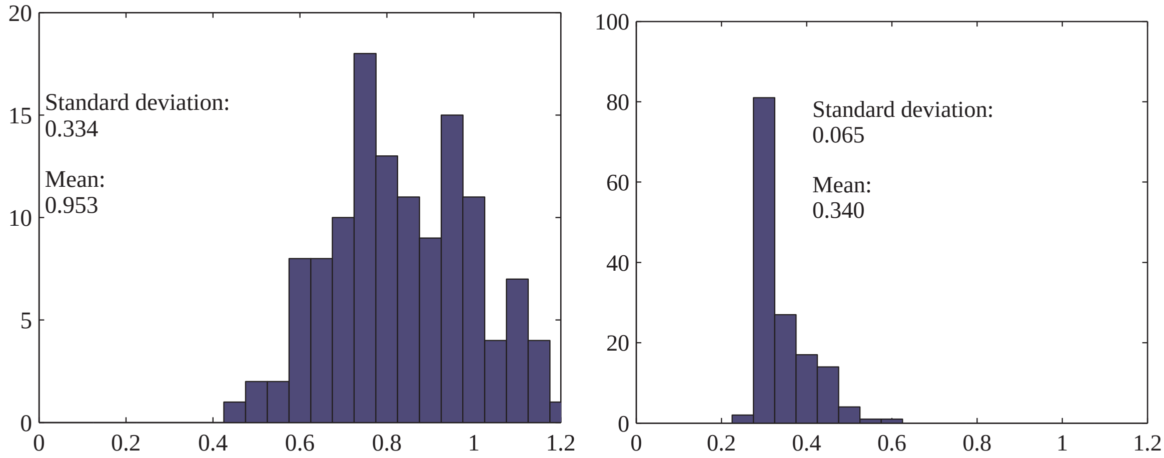
Notes: The table gives cross-sectional correlations between sectoral descriptive statistics. We report the standard deviation (sd) of inflation (π_{it}), the common component ($\boldsymbol{\lambda}_i \mathbf{C}_t$), the idiosyncratic component (e_{it}), and the fraction of the latter two. In addition, the R^2 gives the share of variation in π_{it} explained by $\boldsymbol{\lambda}_i \mathbf{C}_t$, FPC_i denotes the frequency of price changes obtained from Kaufmann (2009) and $speed_i^{macro,idio}$ gives the speed of response to macroeconomic and idiosyncratic shocks, respectively.

BGM.

Looking at correlations between the descriptive statistics reported in Table 2, we find support for both theoretical models. On the one hand, the R^2 is negatively correlated with the volatility of the idiosyncratic component (column 3). That is, little of the inflation variance is explained by the common components in those sectors with volatile idiosyncratic components. In support of the rational inattention model, we may argue that firms facing volatile idiosyncratic shocks react less strongly to macroeconomic shocks. On the other hand, the volatility of the idiosyncratic component is positively correlated with the volatility of the common component (column 2). Firms which either respond strongly to (or face large) idiosyncratic shocks, respond strongly to macroeconomic shocks also. A multi-sector model with infrequent price adjustments is more in line with this observation. For example, for a given size of menu costs, a higher volatility of idiosyncratic shocks would imply that these menu costs would be paid more often and therefore, firms would react more readily and more strongly also to macroeconomic shocks.

In addition, the table contains correlation coefficients for the average quarterly frequency of price changes in sector i (FPC_i) and the speeds of responses to idiosyncratic and macroeconomic shocks, respectively. The frequency of price changes is based on micro data

Figure 2: *Histogram of speed of response*



(a) Idiosyncratic shock (b) Macroeconomic shock

from Kaufmann (2009).[9] Following MMW, we define the speed of response in sector i as

$$\text{speed}_i = \frac{\sum_{q=0}^{2} |\text{resp}_{i,q}|}{\sum_{q=5}^{7} |\text{resp}_{i,q}|} \quad , \tag{3}$$

where $\text{resp}_{i,q}$ denotes the impulse response after q quarters for sector i. This measure of speed captures the reaction of sectoral prices after two quarters relative to the reaction between five and seven quarters.

The additional statistics in Table 2 support the multi-sector sticky-price model by Carvalho and Lee (2011). In line with the predictions of this model we find that the sectoral speeds of responses to macroeconomic shocks correlates positively with the sectoral frequencies of price changes. As their model predicts, the correlation is higher for the speeds of responses to macroeconomic shocks than to idiosyncratic shocks. Moreover, the correlation between the speeds of responses to idiosyncratic and macroeconomic shocks is positive. Finally, Carvalho and Lee (2011) predict a tighter distribution of the speed of responses to macroeconomic shocks than to idiosyncratic shocks. This is supported by Figure 2. The robustness analysis will show, however, that the latter result depends on the specific factor

[9] We updated the statistics for the period 1994 to 2007. In some cases we have aggregated the statistics to a higher level, consistent with the sectoral price indices used in the factor model. Since we do not have micro data on all components all results involving the micro data are based on 114 observations instead of 147.

model used.

Simple correlations can be misleading because we may fail to control for other sector-specific factors and therefore the results may be biased. As MMW emphasise, for example, a rational inattention model predicts that sectors with more volatile sectoral inflation due to idiosyncratic shocks display a smaller response to macroeconomic shocks but only after controlling for the volatility of sectoral inflation due to macroeconomic shocks. In the next section we conduct a regression analysis, where we examine the sectoral price facts while controlling for a variety of other factors.

3.2 Cross-sectional analysis

Following BGM and MMW, the size and speed of the impulse responses in a given sector can be regressed on the descriptive statistics from Section 3.1. These simple cross-sectional regressions can be motivated by a special case of the rational inattention model by Mackowiak and Wiederholt (2009). This model predicts that price responses to macroeconomic shocks are smaller and slower in sectors with idiosyncratic shocks being relatively volatile compared to macroeconomic shocks. Assuming that aggregate demand and idiosyncratic shocks follow independent white noise processes, there is an analytical solution for the optimal price level:

$$p_t^* \quad = \quad (1 - 2^{-\kappa}\frac{\hat{\pi}_{14}}{\hat{\pi}_{13}}\frac{\sigma_z}{\sigma_q})q_t \quad , \tag{4}$$

where κ is the maximum amount of information that can be processed in a time period, $\hat{\pi}_{14}/\hat{\pi}_{13}$ gives the relative sensitivity of profits to idiosyncratic and macroeconomic shocks, σ_z/σ_q denotes the relative volatility of idiosyncratic and macroeconomic shocks, and q_t is nominal aggregate demand. It follows that the response of the price level to a nominal aggregate demand shock amounts to

$$\frac{\partial p_t^*}{\partial q_t} \quad = \quad 1 - 2^{-\kappa}\frac{\hat{\pi}_{14}}{\hat{\pi}_{13}}\frac{\sigma_z}{\sigma_q} \quad . \tag{5}$$

The equation shows that, ceteris paribus, a high volatility of idiosyncratic shocks reduces the responsiveness of prices to macroeconomic shocks. Thus, for this special case of the rational inattention model, a specification including the ratio between the volatility of sectoral inflation due to idiosyncratic and macroeconomic shocks is appropriate. We therefore regress the size of the response to a macroeconomic shock on the volatility of the common and idiosyncratic components. In addition, we include as interaction terms the fraction of the two. Equation (5) shows that a higher volatility of idiosyncratic shocks relative to macroeconomic shocks leads to a smaller response to the macroeconomic shock. The rational inattention model predicts the same relationship for the speed of response although we cannot show this for the simple case above (see Mackowiak and Wiederholt, 2009; Mackowiak et al., 2009).

From our factor model, we obtain an estimate of the size of the response to a macroeconomic shock in sector i. In addition, we obtain an estimate of the volatility of sectoral inflation due to macroeconomic shocks, $\mathrm{sd}(\boldsymbol{\lambda}_i \mathbf{C}_t)$, and idiosyncratic shocks, $\mathrm{sd}(e_{it})$. These estimates reflect both, the volatility of the shocks themselves and the responsiveness of profits to the corresponding shocks. This becomes clear if we note that the estimated volatility of the common component varies across sectors while the volatility of macroeconomic shocks cannot vary across sectors by definition. Therefore, the cross-sectional variation of the common component is naturally interpreted as cross-sectional variation in $\hat{\pi}_{13}$, the sensitivity of profits to macroeconomic shocks. But also, the sensitivity of profits to idiosyncratic conditions may differ across sectors. As additional control variables, we include the sectoral import share as a measure of openness, a sectoral dummy for services, a dummy for administered prices, a dummy for tradable goods, and the relative price level to 15 European countries as a measure of competitive pressures. The coefficients of these additional control variables are not reported for reasons of brevity.

Table 3 gives regressions of the sectoral price responses to a macroeconomic shock after four quarters on time-series properties of the corresponding sectoral inflation rates. The response to a macroeconomic shock increases with the volatility of the idiosyncratic component (column 1). The coefficient is significantly positive. This is not in line with the rational inattention model but more in line with a sticky-price model. However, this result may driven by the fact that we fail to control for the sensitivity of profits to macroeconomic shocks in a given sector.

Table 3: *Size of response to a macroeconomic shock*

$\text{resp}_{i,4}^{macro}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{sd}(e_{it})$	0.454***		-0.076*					
	[0.052]		[0.038]					
$\text{sd}(\boldsymbol{\lambda}_i \mathbf{C}_t)$		2.993***	3.204***					
		[0.131]	[0.179]					
$\frac{\text{sd}(e_{it})}{\text{sd}(\boldsymbol{\lambda}_i \mathbf{C}_t)}$				-0.071				-0.228***
				[0.057]				[0.041]
FPC_i					2.721***		2.761**	4.031***
					[1.022]		[1.057]	[1.087]
Size_i						0.502	-0.903	
						[2.259]	[1.876]	
Constant	2.167***	0.627***	0.538***	2.385***	2.114***	2.216***	2.160***	1.982***
	[0.387]	[0.180]	[0.178]	[0.374]	[0.422]	[0.437]	[0.442]	[0.342]
Observations	147	147	147	147	114	114	114	114
R^2	0.36	0.86	0.86	0.07	0.24	0.06	0.25	0.39

Notes: The table gives cross-sectional regressions of the price responses to a macroeconomic shock after four quarters. The explanatory variables are the standard deviations of the idiosyncratic, $\text{sd}(e_{it})$, and common components, $\text{sd}(\boldsymbol{\lambda}_i \mathbf{C}_t)$, the fraction of the two, the frequency of price changes (FPC_i), and the average absolute size of price changes within a given sector item (Size_i). The responses and standard deviations are measured in percent, the frequency is measures as a ratio and the size of price adjustments is measured in rates of changes. Additional control variables are not reported for brevity. The coefficients are estimated by OLS. Robust standard errors are given in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

As MMW emphasise, we should control for the volatility of the common component because the rational inattention model predicts a positive relationship between the size of the response to macroeconomic shocks and the volatility of sectoral inflation due to macroeconomic shocks. Indeed, we find a positive relationship in column (2). Columns (3) and (4) therefore include both, the volatility of the idiosyncratic component as well as the volatility of the common component. Column (4) gives a more restricted specification which matches the rational inattention model (see equation 5). Column (3) supports the rational inattention model as we find a negative coefficient for the volatility of the idiosyncratic component; but the coefficient is only significant at the 10% level. In addition, most of the cross-sectional variation in the size of responses is driven by cross-sectional heterogeneity in the volatility due to macroeconomic shocks. The R^2 in column (2) amounts to 0.86 and it increases only marginally when we include the volatility due to idiosyncratic shocks in column (3). The specification which is more closely related to the theoretical model is shown in column (4). Although the coefficient on the relative volatility of the idiosyncratic and common component is negative it is not significant.

In a model with sticky prices the size and speed of the response is the same for both kinds of shocks and mostly determined by the sectoral frequency of price changes. Differences in the responsiveness to both kinds of shocks can be modelled by combining across-sector pricing complementarity with within-sector pricing substitutability (Carvalho and Lee, 2011). More generally, a model with sticky prices suggests that the response to macroeconomic shocks would be fast in those sectors with a frequent price adjustments. Therefore, we expect a positive correlation between the size and speed of responses to macroeconomic shocks and the frequency of price adjustments.

Column (5) shows that a higher frequency of price changes, that is a lower degree of price stickiness, implies a larger response to a macroeconomic shock. The frequency of price changes explains about one quarter of the cross-sectional variation and the coefficient is highly significant. Moreover, columns (7) and (8) show that the result is robust if we include the absolute size of price adjustments and the relative volatility of sectoral inflation due to idiosyncratic and macroeconomic shocks. Mackowiak and Wiederholt (2009) note that a shortcoming of the rational inattention model is that it cannot explain why prices remain fixed for some time. They conjecture, that a combination of sticky prices and rational inattention may be a natural extension. Column (8) supports such a combination as the coefficient on the relative volatility of sectoral inflation due to idiosyncratic and macroeconomic shocks is significantly negative only once we control for the frequency of price changes.

Following MMW we replicate the results for the speed of response to a macroeconomic shock as the dependent variable. The results are similar and more consistent with a sticky-price model than with a rational inattention model (Table 4). In fact, the coefficient on the relative volatility of sectoral inflation due to idiosyncratic and macroeconomic shocks is now significantly positive, suggesting that in sectors with a more volatile idiosyncratic component macroeconomic shocks are incorporated faster (column 4). This still holds if we control for the frequency of price changes (column 8). Meanwhile, the frequency of price

Table 4: *Speed of response to a macroeconomic shock*

speed_i^{macro}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{sd}(e_{it})$	0.023***		0.022**					
	[0.008]		[0.009]					
$\text{sd}(\boldsymbol{\lambda}_i \mathbf{C}_t)$		0.066***	0.003					
		[0.020]	[0.028]					
$\frac{\text{sd}(e_{it})}{\text{sd}(\boldsymbol{\lambda}_i \mathbf{C}_t)}$				0.014***				0.009**
				[0.004]				[0.004]
FPC_i					0.147***		0.147***	0.094
					[0.048]		[0.050]	[0.061]
Size_i						0.076	0.001	
						[0.127]	[0.141]	
Constant	0.209***	0.181***	0.208***	0.216***	0.197***	0.200***	0.197***	0.202***
	[0.031]	[0.038]	[0.037]	[0.031]	[0.033]	[0.035]	[0.031]	[0.033]
Observations	147	147	147	147	114	114	114	114
R^2	0.30	0.23	0.30	0.28	0.24	0.14	0.24	0.29

Notes: The table gives cross-sectional regressions of speed of responses to a macroeconomic shock. The explanatory variables are the standard deviations of the idiosyncratic, $\text{sd}(e_{it})$, and common components, $\text{sd}(\boldsymbol{\lambda}_i \mathbf{C}_t)$, the fraction of the two, the frequency of price changes (FPC_i), and the average absolute size of price changes within a given sector item (Size_i). The responses and standard deviations are measured in percent, the frequency is measures as a ratio and the size of price adjustments is measured in rates of changes. Additional control variables are not reported for brevity. The coefficients are estimated by OLS. Robust standard errors are given in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

changes explains one quarter of the cross-sectional variation of the speed of response (column 5).

Up to now, we treated the frequency of price changes as an exogenous regressor explaining the size and speed of responses to macroeconomic shocks. By doing so, we do not distinguish between a Calvo (1983) model with an exogenously given frequency of price changes and a menu-cost model with more frequent price adjustments in sectors with more volatile shocks.[10] For a given size of the menu cost, larger shocks imply that the benefit of adjusting the price exceeds the associated costs more often. Therefore, we would expect a positive correlation between the volatility of sectoral inflation to macroeconomic and idiosyncratic shocks and the frequency of price changes.

Table 5 shows that there is indeed a significantly positive relationship between the

[10] Menu-cost models with one or more sectors are presented in Dotsey et al. (2006), Golosov and Lucas (2007), Gertler and Leahy (2008), or Nakamura and Steinsson (2010).

Table 5: *Frequency of price changes*

FPC_i	(1)	(2)	(3)	(4)
$\text{sd}(e_{it})$	0.097***		0.094***	
	[0.010]		[0.015]	
$\text{sd}(\boldsymbol{\lambda}_i \mathbf{C}_t)$		0.299***	0.015	
		[0.088]	[0.055]	
$\frac{\text{sd}(e_{it})}{\text{sd}(\boldsymbol{\lambda}_i \mathbf{C}_t)}$				0.040***
				[0.011]
Constant	0.036	-0.117	0.028	0.060
	[0.058]	[0.081]	[0.062]	[0.070]
Observations	114	114	114	114
R^2	0.63	0.35	0.63	0.27

Notes: The table gives cross-sectional regressions using the frequency of price changes as dependent variable. The explanatory variables are the standard deviations of the idiosyncratic, $\text{sd}(e_{it})$, and common components, $\text{sd}(\boldsymbol{\lambda}_i \mathbf{C}_t)$, and the fraction of the two. The standard deviations are measured in percent, the frequency of price adjustments is measured as a ratio. Additional control variables are not reported for brevity. The coefficients are estimated by OLS. Robust standard errors are given in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

frequency of price changes and the standard deviation of the idiosyncratic component. More than 60% of the variation in the frequency of price changes can be explained by cross-sectional differences in the volatility of the idiosyncratic component. Also, the coefficient on the standard deviation of the common component is significant. Column (3) shows, however, that the volatility of the common component does not add much to the explanatory power of the standard deviation of the idiosyncratic component; the R^2 is essentially unchanged from column (1). Finally, the fraction of the two volatility measures also has a significantly positive coefficient. Overall, these results are in line with the idea that macroeconomic shocks themselves do not trigger many price adjustments. But these macro shocks are incorporated quicker in sectors where prices are adjusted more often because of idiosyncratic shocks.

3.3 Robustness analysis

BGM and MMW are two seminal contributions analysing sectoral price data with factor models estimated on US data. The findings by MMW are broadly consistent with the rational inattention model. Our reading of BGM is that the findings are more in line with a sticky-price model.[11] The findings presented in this paper are mostly in line with a multi-sector sticky-price model and less in line with the rational inattention model. Therefore, this section aims to explain why our results, which are derived based on the BGM approach, differ from MMW. As conjectured by Carvalho and Lee (2011), the two different modelling approaches have important consequences for the results. The approach used here differs from MMW in three broad aspects.

First, we use different cross-sectional specifications. For each regression, MMW include as regressors only the variables of main interest. By contrast, we impose more structure on the regression by using interaction terms which are consistent with the rational inattention model. In addition, we include a set of dummy variables to control for observed sectoral characteristics.

Second, we estimate our factor model on a different information set. We use Swiss consumer price data and additionally include a broad set of macroeconomic variables. MMW use only sectoral consumer price data from the US. Notice that adding macroeconomic variables in addition to price data should not matter in large samples. The common factors are identified as the number of cross-section items and the number of time periods tend to infinity (see Stock and Watson, 2002a). However, in finite samples, the macroeconomic data may help to identify the common component of the sectoral inflation rates. An additional difference is that MMW replace outliers, which are defined as observations which are larger than four times the standard deviation of the corresponding sectoral inflation rate, with the average sectoral inflation rate.

Third, we use a different factor model. Our model is set up in terms of several static factors, while MMW use one dynamic factor. Given that we use the correct number of static and dynamic factors in the two models, this choice should not affect the results, at least in large samples. The reason is that a dynamic factor model can be rewritten as a static factor model and therefore, we should be able to consistently estimate the common component of inflation using both representations (see e.g. Stock and Watson, 2002a; Bai and Ng, 2007).

[11] In particular, they find a clear positive relationship between the volatility of the idiosyncratic component and the sectoral frequencies of price changes. Moreover, they find a stronger response to macroeconomic shocks in sectors with a volatile idiosyncratic component.

Then, MMW use a Bayesian approach to jointly estimate the common components as well as the dynamics of the factor model. They assume that the common components follow monthly MA(24) processes while the idiosyncratic components follow AR(6) processes. We use a principal components approach to estimate the common components. The dynamics of the idiosyncratic and common components are estimated in a second step by fitting autoregressive processes. The advantage of the Bayesian approach is that it is straightforward to account for estimation uncertainty for all statistics we derive from the factor model. The advantage of the principle components approach is that we can consistently estimate the common components under fairly general conditions (see Stock and Watson, 2002b).

Our strategy to test the robustness of our results regarding the two different approaches is as follows. First, we establish a benchmark using the MMW approach on our Swiss data set.[12] The MMW benchmark uses only Swiss price data, excludes outliers and uses the same specification of the factor model as MMW use for quarterly data. Then, we obtain the results using the BGM approach for various specifications making them increasingly similar to the MMW benchmark. In particular, we change one difference at a time but keep the changes in subsequent specifications. The quantitative results are not reprinted here for reasons of brevity and are available upon request. We summarise the key results qualitatively in Table 6.

The main differences between the BGM benchmark (column 1) and the MMW benchmark (column 8) concern the cross-sectional dispersion of the speed of responses to macroeconomic and idiosyncratic shocks. The BGM approach yields a tighter distribution for the speed of responses due to macroeconomic than due to idiosyncratic shocks. The MMW approach yields a wider distribution (see also Carvalho and Lee, 2011). This divergence does not change for any of our alternative approaches and is therefore related to using two different factor models.

Another divergence emerges for the relationship between the speed of response to macroeconomic shocks and the relative volatility of the idiosyncratic and common components of sectoral inflation. The BGM approach gives a positive correlation which is not consistent with the rational inattention model. But, if we exclude outliers from the data set (columns $4-7$), the results become inconclusive. Meanwhile, the MMW approach favours

[12]We thank the authors for making their program code available on the Internet.

Table 6: *Qualitative summary of key results*

	BGM							MMW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Predictions of rational inattention model (Mackowiak and Wiederholt, 2009; Mackowiak et al., 2009)								
Slower response to macroeconomic shocks than to idiosyncratic shocks	+	+	+	+	+	+	+	+
Smaller response to macroeconomic shocks if idiosyncratic component is more volatile than common component	0	+/0	0	+	+	0	0	+
Slower response to macroeconomic shocks if idiosyncratic component is more volatile than common component	-	-	-/0	0	0	0	0	+
If the idiosyncratic component is on average more volatile than the common component, the cross-sector dispersion of the speed of response to idiosyncratic shocks is tighter than the one to macroeconomic shocks	-	-	-	-	-	-	-	+
Predictions of multi-sector model with infrequent price adjustments (Nakamura and Steinsson, 2010; Carvalho and Lee, 2011)								
Slower response to macroeconomic shocks than to idiosyncratic shocks	+	+	+	+	+	+	+	+
Positive correlation between the size of response to a macroeconomic shock and the sectoral frequencies of price changes	+	+	+	+	+	+	+	0
Positive correlation between the speed of response to a macroeconomic shock and the sectoral frequencies of price changes	+	+	+	+	+	+	+	+
Positive correlation between standard deviation of the common component and the frequency of price changes	+	+	+	+	+/0	+	+	+
Positive correlation between standard deviation of the idiosyncratic component and the frequency of price changes	+	+	+	+	+	+/0	+	+
Positive correlation between the speed of responses to macroeconomic and idiosyncratic shocks	+	+	+	+	+	+	+	+/0
Tighter cross-sectional variation of the sectoral speeds of responses to macroeconomic shocks than to sector-specific shocks	+	+	+	+	+	+	+	-

Notes: The table summarises the key results across eight different specifications using the factor models by BGM and MMW. +/0/- indicate that the results are supportive/inconclusive/non-supportive of the theoretical predictions given in the first column. Columns (1) and (8) are the benchmark specifications using Swiss data, applying the BGM and MMW approaches, respectively. The alternative specifications, (2)-(7), increasingly make the BGM benchmark more comparable to the MMW benchmark. The differences changed are: (2) no additional control variables; (3) only price data; (4) excluding outliers; (5) US price data set used by MMW; (6) US price data set used by BGM; (7) Swiss data set with more static factors.

the rational inattention model by signalling a negative correlation. The treatment of outliers relates to De Graeve and Walentin (2011) who discuss the role of measurement error for the robustness of sectoral price facts.[13] Based on an estimate of the idiosyncratic component cleaned by a moving average component, which captures temporary price movements such as sales and measurement errors, they argue that some of the BGM findings are mere artefacts. However, using their method one cannot distinguish between measurement error, sales and any other temporary factors affecting sectoral prices. Thus, in our view, it remains an open question, whether the outliers excluded by MMW and temporary price movements excluded by De Graeve and Walentin (2011) reflect measurement errors that we should ignore in our analysis or whether they are because of actual price-setting decisions.

We replicated specification (4) with the US data sets used by BGM and MMW (columns 6 and 7).[14] These results support the view that the diverging results between BGM and MMW are not mainly due to different data sets. Using the BGM approach we obtain similar results for both data sets. We tend to favour a sticky-price model over a rational inattention model. This is in line with our previous results which are derived using only Swiss data for all specifications.

Some of the results are sensitive to the choice of the factor model. However, it seems inappropriate to prefer a specific factor model to another, especially, because the differences should mainly play a role in finite samples. Therefore, we would like to point out that some results are robust across our two benchmarks. These results are broadly in line with the multi-sector sticky-price model presented in Carvalho and Lee (2011). First, the response to macroeconomic shocks is slower than the response to idiosyncratic shocks. Second, the speed of response to macroeconomic shocks is faster in sectors with a higher frequency of price changes. Third, we observe a positive correlation between the volatility of both, the idiosyncratic and common components, and the frequency of price changes.

[13]Using BGM's US data set, they estimate that 11% of the variance of inflation is due to measurement error.

[14]We thank the authors for making available the data on the Internet. In addition, we thank Marc Giannoni for providing the matching between the frequencies of price changes by Nakamura and Steinsson (2008) and their sectors.

4 Conclusions

This paper confronts two popular models of price-setting behaviour with stylised facts from sectoral price data. We use an approximate factor model to decompose sectoral inflation in Switzerland into an idiosyncratic and a common component. This decomposition allows us to analyse the sectoral price responses to idiosyncratic and macroeconomic shocks.

Flexible prices at the micro level are consistent with persistent aggregate inflation because the price-setting behaviour depends on the nature of the underlying shock. While sectoral prices react only weakly and slowly to macroeconomic shocks, they react relatively strongly and quickly to idiosyncratic shocks. With aggregation, idiosyncratic shocks cancel each other out such that the sluggish behaviour of the aggregate CPI is mainly driven by macroeconomic shocks. Although the response to macroeconomic shocks is sluggish on average, there is a lot of heterogeneity across sectors.

We analyse this heterogeneity in more detail and show that the relative volatility of sectoral inflation due to idiosyncratic and macroeconomic shocks does not mute the size and speed of responses to macroeconomic shocks. This finding stands in contrast to the rational inattention model of price setting, which implies that firms facing idiosyncratic shocks which are volatile relative to macroeconomic shocks do not fully respond to macroeconomic shocks, because they pay less attention to them. Our results are more in line with implications of sticky price models, in which macroeconomic shocks feed quickly into prices in those sectors with frequent price adjustments. Indeed, sectors with a higher frequency of price changes react more strongly and more swiftly to macroeconomic shocks. Taken together, multi-sector models featuring sticky prices are more in line with our empirical findings rather than models of rational inattention.

References

Altissimo, F., B. Mojon, and P. Zaffaroni (2009): "Can Aggregation Explain the Persistence of Inflation?" *Journal of Monetary Economics*, 56, 231–241.

Bai, J. and S. Ng (2002): "Determining the Number of Factors in Approximate Factor Models," *Econometrica*, 70, 191–221.

——— (2007): "Determining the Number of Primitive Shocks in Factor Models," *Journal of Business & Economic Statistics*, 25, 52–60.

Beck, G. W., K. Hubrich, and M. Marcellino (2011): "On the Importance of Sectoral and Regional Shocks for Price-Setting," Working Paper Series 1334, European Central Bank.

Boivin, J., M. P. Giannoni, and I. Mihov (2009): "Sticky Prices and Monetary Policy: Evidence from Disaggregated US Data," *American Economic Review*, 99, 350–84.

Calvo, G. A. (1983): "Staggered Pricing in a Utility Maximizing Framework," *Journal of Monetary Economics*, 12, 383–398.

Carvalho, C. (2006): "Heterogeneity in Price Setting and the Real Effects of Monetary Shocks," *Frontiers of Macroeconomics*, 2, 1–56.

Carvalho, C. and J. W. Lee (2011): "Sectoral Price Facts in a Sticky-Price Model," Staff Reports 495, Federal Reserve Bank of New York.

Ciccarelli, M. and B. Mojon (2010): "Global Inflation," *The Review of Economics and Statistics*, 92, 524–535.

De Graeve, F. and K. Walentin (2011): "Stylized (Arte) Facts on Sectoral Inflation," Working Paper Series 254, Sveriges Riksbank.

Dotsey, M., R. G. King, and A. L. Wolman (2006): "Inflation and Real Activity with Firm-Level Productivity Shocks: A Quantitative Framework." Mimeo.

ELMER, S. AND T. MAAG (2009): "The Persistence of Inflation in Switzerland: Evidence from Disaggregate Data," Working Paper 09-235, KOF Swiss Economic Institute, ETH Zurich.

FÖRSTER, M. AND P. TILLMANN (2013): "Local Inflation: Reconsidering the International Comovement of Inflation," Joint Discussion Paper Series in Economics 03-2013, University of Göttingen.

GERTLER, M. AND J. LEAHY (2008): "A Phillips Curve with an S,s Foundation," *Journal of Political Economy*, 116, 533–572.

GIANNONE, D., L. REICHLIN, AND L. SALA (2005): "Monetary Policy in Real Time," in *NBER Macroeconomics Annual 2004*, National Bureau of Economic Research, vol. 19 of *NBER Chapters*, 161–224.

GOLOSOV, M. AND R. E. LUCAS (2007): "Menu Costs and Phillips Curves," *Journal of Political Economy*, 115, 171–199.

HUWILER, M. AND D. KAUFMANN (2013): "Combining Disaggregate Forecasts for Inflation: The SNB's ARIMA Model," Economic Studies 2013-07, Swiss National Bank.

KAUFMANN, D. (2009): "Price-Setting Behaviour in Switzerland: Evidence from CPI Micro Data," *Swiss Journal of Economics and Statistics*, 145, 293–349.

KAUFMANN, D. AND S. LEIN (2011): "Sectoral Inflation Dynamics, Idiosyncratic Shocks and Monetary Policy," Working Paper Series 2011-7, Swiss National Bank.

KAUFMANN, D. AND S. M. LEIN (2012): "Is There a Swiss Price Puzzle?" *Swiss Journal of Economics and Statistics*, 148, 57–75.

MACKOWIAK, B., E. MOENCH, AND M. WIEDERHOLT (2009): "Sectoral Price Data and Models of Price Setting," *Journal of Monetary Economics*, 56, S78–S99.

MACKOWIAK, B. AND M. WIEDERHOLT (2009): "Optimal Sticky Prices under Rational Inattention," *American Economic Review*, 99, 769–803.

Mackowiak, B. A. and F. Smets (2008): "On Implications of Micro Price Data for Macro Models," Discussion Paper 6961, CEPR.

Mumtaz, H., P. Zabczyk, and C. Ellis (2009): "What Lies Beneath: What Can Disaggregated Data Tell us About the Behaviour of Prices?" Working Paper 364, Bank of England.

Nakamura, E. and J. Steinsson (2008): "Five Facts About Prices: A Reevaluation of Menu Cost Models," *Quarterly Journal of Economics*, 123.

——— (2010): "Monetary Non-Neutrality in a Multisector Menu Cost Model," *The Quarterly Journal of Economics*, 125, 961–1013.

Stock, J. H. and M. W. Watson (2002a): "Forecasting Using Principal Components from a Large Number of Predictors," *Journal of the American Statistical Association*, 97, 1167–1179.

——— (2002b): "Macroeconomic Forecasting Using Diffusion Indexes," *Journal of Business & Economic Statistics*, 20, 147–62.