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# Sectoral price data and models of price setting ☆

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A B S T R A C T

In the median sector, 100 percent of the long-run response of the sectoral price index to a sector-specific shock occurs in the month of the shock. The standard Calvo model and the standard sticky-information model can match this finding only under extreme assumptions concerning the profit-maximizing price. The rational-inattention model of Maćkowiak and Wiederholt [2009a. Optimal sticky prices under rational inattention. American Economic Review 99, 769–803] can match this finding without an extreme assumption concerning the profit-maximizing price. Furthermore, there is little variation across sectors in the speed of response of sectoral price indexes to sector-specific shocks. The rational-inattention model matches this finding, while the Calvo model predicts too much cross-sectional variation.



## 1. Introduction

Over the last 20 years, there has been a surge in research on macroeconomic models with price stickiness. In these models, price stickiness arises either from adjustment costs (e.g. the Calvo model and the menu cost model) or from some form of information friction (e.g. the sticky-information model and the rational-inattention model). Models of price stickiness are often evaluated by looking at aggregate data. Recently models of price stickiness have been evaluated by looking at micro data. This paper evaluates models of price stickiness by studying sectoral data. A statistical model for sectoral inflation rates is estimated and used to compute impulse responses of sectoral price indexes to aggregate shocks and to sector-specific shocks. This paper proceeds by analyzing whether different models of price setting can match the empirical impulse responses.

The statistical model that is estimated is the following. The inflation rate in a sector equals the sum of two components, an aggregate component and a sector-specific component. The parameters in the aggregate component and in the

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sector-specific component may differ across sectors. An innovation in the aggregate component may affect the inflation rates in all sectors. An innovation in the sector-specific component affects only the inflation rate in this sector. The statistical model is estimated using monthly sectoral consumer price data from the US economy for the period 1985–2005. The data are compiled by the Bureau of Labor Statistics (BLS). From the estimated statistical model, one can compute impulse responses of the price index for a sector to an innovation in the aggregate component and to an innovation in the sector-specific component.

The median impulse responses have the following shapes. After a sector-specific shock, 100 percent of the long-run response of the sectoral price index occurs in the month of the shock, and the response equals the long-run response in all months following the shock. By contrast, after an aggregate shock, only 15 percent of the long-run response of the sectoral price index occurs in the month of the shock, and the response gradually approaches the long-run response in the months following the shock. Another way of summarizing the median impulse responses is as follows. The sector-specific component of the sectoral inflation rate is essentially a white noise process, while the aggregate component of the sectoral inflation rate is positively autocorrelated.

This paper proceeds by studying whether the standard Calvo model, the standard sticky-information model, and the rational-inattention model developed in Maćkowiak and Wiederholt (2009a) can match the median impulse response of sectoral price indexes to sector-specific shocks. The focus is on the response to sector-specific shocks, because it is well known that all three models can match the median impulse response of sectoral price indexes to aggregate shocks, for reasonable parameter values. In fact, the models have been developed to explain the slow response of prices to aggregate shocks. What we find interesting is that these models emphasize different reasons for why the response of prices to aggregate shocks is slow: infrequent price adjustment (Calvo model) and information frictions (sticky-information model and rational-inattention model). This paper evaluates the plausibility of the reason emphasized by a given model by asking whether the model can match the median impulse response of sectoral price indexes to sector-specific shocks.

Recall that this impulse response looks like the impulse response function of a random walk: the sectoral price index jumps on the impact of a sector-specific shock, and stays there. Proposition 1 shows that the standard Calvo model can match the median impulse response of sectoral price indexes to sector-specific shocks only under an extreme assumption concerning the response of the profit-maximizing price to sector-specific shocks. After a sector-specific shock, the profit-maximizing price needs to jump by about $(1/\lambda^2)x$ in the month of the shock, and then has to jump back to $x$ in the month following the shock to generate a response equal to $x$ of the sectoral price index on impact and in all months following the shock. Here $\lambda$ denotes the fraction of firms that can adjust their prices in a month. Proposition 2 provides a similar, though less extreme, result for the standard sticky-information model developed in Mankiw and Reis (2002). After a sector-specific shock, the profit-maximizing price needs to jump by $(1/\lambda)x$ in the month of the shock, and then has to decay slowly to $x$ to generate a response equal to $x$ of the sectoral price index on impact and in all months following the shock. Here $\lambda$ denotes the fraction of firms that can update their pricing plans in a month. By contrast, the rational-inattention model developed in Maćkowiak and Wiederholt (2009a) matches the median impulse response of sectoral price indexes to sector-specific shocks without an extreme assumption concerning the response of the profit-maximizing price to sector-specific shocks. The reason is simple. According to the estimated statistical model, sector-specific shocks are on average much larger than aggregate shocks. Under these circumstances, the theoretical model predicts that decision-makers in firms pay significantly more attention to sector-specific conditions than to aggregate conditions, implying that prices respond quickly to sector-specific shocks and slowly to aggregate shocks.

The different models of price setting are also evaluated on their ability to predict the right amount of variation across sectors in the speed of response of sectoral price indexes to sector-specific shocks. According to the estimated statistical model, there is little variation across sectors in the speed of response of sectoral price indexes to sector-specific shocks. It turns out that a multi-sector Calvo model calibrated to the sectoral monthly frequencies of price changes reported in Bils and Klenow (2004) predicts too much cross-sectional variation in the speed of response to sector-specific shocks. By contrast, the rational-inattention model developed in Maćkowiak and Wiederholt (2009a) correctly predicts little cross-sectional variation in the speed of response to sector-specific shocks. The reason is as follows. According to the theoretical model, decision-makers in firms in the median sector are already paying so much attention to sector-specific conditions that they track sector-specific conditions almost perfectly. Paying even more attention to sector-specific conditions has little effect on the speed of response of prices to sector-specific shocks.

This paper is related to Boivin et al. (2009). They use a factor augmented vector autoregressive model to study sectoral data published by the Bureau of Economic Analysis (BEA) on personal consumption expenditure. Boivin et al. (2009) found that sectoral price indexes respond quickly to sector-specific shocks and slowly to aggregate shocks, and that sector-specific shocks account for a dominant share of the variance in sectoral inflation rates. This paper differs from Boivin et al. (2009) in several ways. First of all, the statistical model, estimation methodology, and dataset are different. Second, this paper characterizes the conditions under which the standard Calvo model, the standard sticky-information model, and the rational-inattention model developed in Maćkowiak and Wiederholt (2009a) can match the median impulse response of sectoral price indexes to sector-specific shocks. Third, this paper estimates the cross-sectional distribution of the speed of response to aggregate shocks and the cross-sectional distribution of the speed of response to sector-specific shocks. These cross-sectional distributions are useful for evaluating models of price setting. Fourth, this paper studies the distribution of sector-specific shocks and discusses the relationship to recent menu cost models.

This paper is also related to Reis and Watson (2007a, b) who used a dynamic factor model to study sectoral data published by the BEA on personal consumption expenditure. The focus of Reis and Watson (2007a, b) is on estimating the numeraire (defined as a common component in prices that has an equiproportional effect on all prices). Furthermore, this paper is related to Kehoe and Midrigan (2007) who studied data from Europe and the United States on sectoral real exchange rates. Kehoe and Midrigan (2007) found much less heterogeneity in the persistence of sectoral real exchange rates in the data than predicted by the Calvo model.

The statistical model in this paper belongs to the class of dynamic factor models. Dynamic factor models have been estimated using maximum-likelihood methods, non-parametric methods based on principal components, and Bayesian methods.[1] This paper uses Bayesian methods. Section 2 explains the contribution to the literature on the estimation of dynamic factor models. Section 2 also describes how the statistical model and estimation methodology differ from the work of Boivin et al. (2009).

This paper is organized as follows. Section 2 presents the statistical model and estimation methodology. Section 3 describes the data. Sections 4 and 5 present the results from the statistical model. Section 6 discusses robustness of the results. Section 7 studies whether the model of Calvo (1983), the sticky-information model of Mankiw and Reis (2002), and the rational-inattention model developed in Maćkowiak and Wiederholt (2009a) can match the estimated impulse responses. Section 8 concludes. Appendix A gives econometric details. Appendices B and C contain proofs of theoretical results.[2]

## 2. Statistical model and estimation methodology

Consider the statistical model

$$\pi_{nt} = \mu_n + A_n(L)u_t + B_n(L)\nu_{nt}, \tag{1}$$

where $\pi_{nt}$ is the month-on-month inflation rate in sector $n$ in period $t$, $\mu_n$ are constants, $A_n(L)$ and $B_n(L)$ are square summable polynomials in the lag operator, $u_t$ is an unobservable factor following a unit-variance Gaussian white noise process, and each $\nu_{nt}$ follows a unit-variance Gaussian white noise process. The processes $\nu_{nt}$ are pairwise independent and independent of the process $u_t$.

It is straightforward to generalize Eq. (1) such that $u_t$ follows a vector Gaussian white noise process with covariance matrix identity. In estimation, this paper considers the case when $u_t$ follows a scalar process and the case when $u_t$ follows a vector process.

Let $\pi_{nt}^A$ denote the aggregate component of the inflation rate in sector $n$, that is,

$$\pi_{nt}^A = A_n(L)u_t.$$

The aggregate component of the inflation rate in sector $n$ is parameterized as a finite-order moving average process. The order of the polynomials $A_n(L)$ is chosen to be as high as computationally feasible. Specifically, the order of the polynomials $A_n(L)$ is set to 24, that is, $u_t$ and 24 lags of $u_t$ enter Eq. (1).

Let $\pi_{nt}^S$ denote the sector-specific component of the inflation rate in sector $n$, that is,

$$\pi_{nt}^S = B_n(L)\nu_{nt}.$$

To reduce the number of parameters to estimate, the sector-specific component of the inflation rate in sector $n$ is parameterized as an autoregressive process:

$$\pi_{nt}^S = C_n(L)\pi_{nt}^S + B_{n0}\nu_{nt},$$

where $C_n(L)$ is a polynomial in the lag operator satisfying $C_{n0} = 0$. In estimation, this paper considers the case when the order of the polynomials $C_n(L)$ equals 6 and the case when the order of the polynomials $C_n(L)$ equals 12.

Before estimation, the sectoral inflation rates are demeaned. Furthermore, the sectoral inflation rates are normalized to have unit variance. These adjustments imply that the estimated model is

$$\tilde{\pi}_{nt} = a_n(L)u_t + b_n(L)\nu_{nt},$$

where $\tilde{\pi}_{nt} = [(\pi_{nt} - \mu_n)/\sigma_{\pi_n}]$ is the normalized inflation rate in sector $n$ in period $t$, and $a_n(L)$ and $b_n(L)$ are square summable polynomials in the lag operator. Here $\sigma_{\pi_n}$ is the standard deviation of the inflation rate in sector $n$. The following relationships hold: $A_n(L) = \sigma_{\pi_n} a_n(L)$ and $B_n(L) = \sigma_{\pi_n} b_n(L)$. This normalization makes it easier to compare impulse responses across sectors. In what follows, this paper refers to coefficients appearing in the polynomials $a_n(L)$ and $b_n(L)$ as "normalized impulse responses".

[1] Maximum likelihood estimation: in frequency domain (Geweke, 1977; Sargent and Sims, 1977; Geweke and Singleton, 1981); in time domain (Engle and Watson, 1981; Stock and Watson, 1989; Quah and Sargent, 1992; Reis, 2006; Reis and Watson, 2007a); quasi-maximum likelihood in time domain (Doz et al., 2006). Non-parametric estimation based on principal components (Forni et al., 2000; Stock and Watson, 2002a, b; Bernanke et al., 2005; Boivin et al., 2009). Bayesian estimation (Otrok and Whiteman, 1998; Kim and Nelson, 1999; Kose et al., 2003; Del Negro and Otrok, 2007).

[2] Appendices, data, and replication code are available on Science Direct.

This paper uses Bayesian methods to estimate the model. In particular, the Gibbs sampler with a Metropolis–Hastings step is used to sample from the joint posterior density of the factors and the model's parameters. Taking as given a Monte Carlo draw of the model's parameters, one samples from the conditional posterior density of the factors given the model's parameters. Here the paper follows Carter and Kohn (1994) and Kim and Nelson (1999). Afterwards, taking as given a Monte Carlo draw of the factors, one samples from the conditional posterior density of the model's parameters given the factors. Here the paper follows Chib and Greenberg (1994). The following prior is used. The prior has zero mean for each factor loading and for each autoregressive coefficient in the sector-specific component of the inflation rate in sector $n$. The prior starts out loose and becomes gradually tighter at more distant lags.[3]

The paper contributes to the branch of the literature on estimation of dynamic factor models using Bayesian methods.[4] The extant papers in this branch assume that factors follow independent autoregressive processes and that the loading of each variable on each factor is a scalar. Instead, here it is assumed that factors follow independent white noise processes and that the loadings of each variable on each factor form a polynomial in the lag operator. See Eq. (1). The former setup implies that, for any pair of variables $i$ and $j$, the impulse response function of variable $i$ to an innovation in a factor is proportional to the impulse response function of variable $j$ to the same innovation. The latter setup implies no such restriction.[5] We believe it is important to allow for the possibility that the impulse response function of a sectoral price index to an aggregate shock differs in shape across sectors. Therefore, we prefer the latter setup.

The use of Bayesian methods offers a specific advantage in the context of our analysis. When one estimates regression relationships using variables derived from the dynamic factor model, Bayesian methods allow one to quantify easily the uncertainty concerning the regression relationships. See Sections 5 and 6. Without Bayesian methods, one typically proceeds as if the point estimate of, say, the standard deviation of sectoral inflation due to sector-specific shocks derived from the dynamic factor model were the truth.[6]

The advantage of principal-component-based estimation of a dynamic factor model, as in Boivin et al. (2009), is that it is straightforward, from the computational point of view, to add more variables. For example, Boivin et al. (2009) added sectoral data on quantities and macroeconomic data.

## 3. Data

This paper uses the data underlying the consumer price index (CPI) for all urban consumers in the United States. The data are compiled by the Bureau of Labor Statistics (BLS). The data are monthly sectoral price indexes. The sectoral price indexes are available at four different levels of aggregation: from least disaggregate (eight "major groups") to most disaggregate (205 sectors).[7] This paper focuses on the most disaggregate sectoral price indexes. For some sectors, price indexes are available for only a short period, often starting as recently as in 1998. This paper focuses on the 79 sectors for which monthly price indexes are available from January 1985. These sectors comprise 68.1 percent of the CPI. Each "major group" is represented. The sample used here ends in May 2005.

The median standard deviation of sectoral inflation in the cross-section of sectors in this paper's dataset is 0.0068. For comparison, the standard deviation of the CPI inflation rate in this paper's sample period is 0.0017. In 76 of 79 sectors, the sectoral inflation rate is more volatile than the CPI inflation rate.

To gain an idea about the degree of comovement in this paper's dataset, one can compute principal components of the normalized sectoral inflation rates. The first few principal components explain only little of the variation in the normalized sectoral inflation rates. In particular, the first principle component explains 7 percent of the variation, and the first five principle components together explain 20 percent of the variation.

These observations suggest that changes in sectoral price indexes are caused mostly by sector-specific shocks.

## 4. Responses of sectoral price indexes to sector-specific shocks and to aggregate shocks

This section reports results from the estimated dynamic factor model (1). The focus is on the benchmark specification in which the factor $u_t$ follows a scalar process and the order of the polynomials $C_n(L)$ equals 6. Two other specifications were also estimated: (i) a specification in which the order of the polynomials $C_n(L)$ equals 12 and (ii) a specification in which $u_t$ follows a bivariate vector process and the order of the polynomials $C_n(L)$ equals 6. It turned out that the specification in which $u_t$ follows a scalar process and the order of the polynomials $C_n(L)$ equals 6 forecasts better out-of-sample compared

[3] See Appendix A available on Science Direct for econometric details, including details of the prior.

[4] See Footnote 1.

[5] An unpublished paper by Justiniano (2004) uses the latter setup and Bayesian methods, like this paper. This paper differs from Justiniano (2004) in that this paper includes a Metropolis–Hastings step in the Gibbs sampler while Justiniano does not. This difference means that, in sampling from the conditional posterior density of the model's parameters given the factors, this paper uses the full likelihood function while Justiniano uses the likelihood function conditional on initial observations.

[6] Bayesian estimation of a dynamic factor model also offers a general advantage compared with estimation based on principal components. One obtains the joint posterior density of the factors and the model's parameters.

[7] The "major groups" are (with the percentage share in the CPI given in brackets): food and beverages (15.4), housing (42.1), apparel (4.0), transportation (16.9), medical care (6.1), recreation (5.9), education and communication (5.9), other goods and services (3.8).

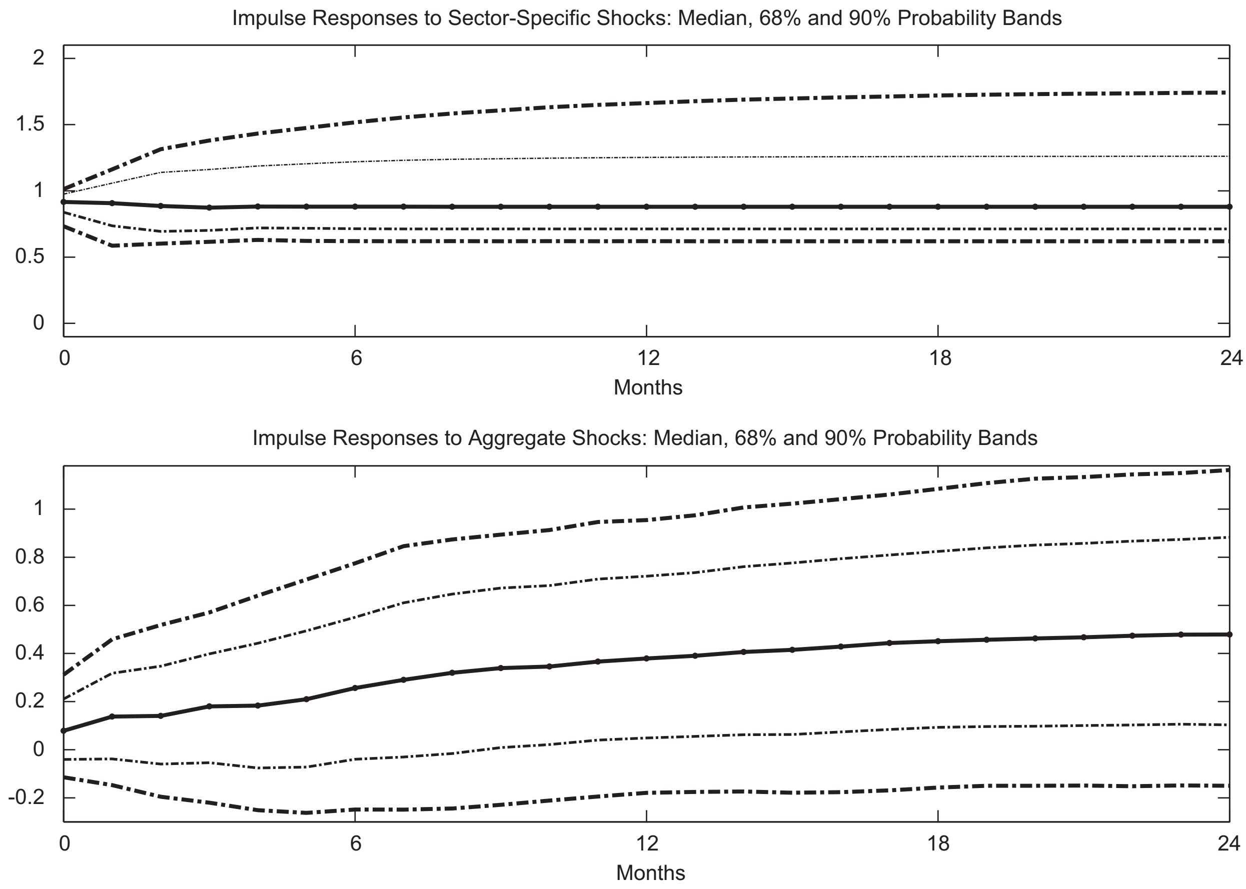


**Fig. 1.** The cross-section of the normalized impulse responses of sectoral price indexes. *Note*: This figure shows the posterior density of the normalized impulse responses of sectoral price indexes to sector-specific shocks (top panel) and to aggregate shocks (bottom panel). The posterior density takes into account variation across sectors and parameter uncertainty. The results reported in this figure are discussed in Section 4.

with the other two specifications. Therefore, this specification was chosen as the benchmark specification. Section 6 discusses the results from the other two specifications. Furthermore, the out-of-sample forecast performance of the dynamic factor model was compared with that of simple, autoregressive models for sectoral inflation. It turned out that (i) the benchmark dynamic factor model forecasts better than the AR(6) model and (ii) the dynamic factor model in which the order of the polynomials $C_n(L)$ equals 12 forecasts better than the AR(12) model. The forecast results show that the dynamic factor model fits the data well.[8]

To begin consider the variance decomposition of sectoral inflation into aggregate shocks and sector-specific shocks. Sector-specific shocks account for a dominant share of the variance in sectoral inflation. In the median sector, the share of the variance in sectoral inflation due to sector-specific shocks equals 90 percent. The sectoral distribution is tight. In the sector that lies at the 5th percentile of the sectoral distribution, the share of the variance in sectoral inflation due to sector-specific shocks equals 79 percent, and in the sector that lies at the 95th percentile of the sectoral distribution, the share of the variance in sectoral inflation due to sector-specific shocks equals 95 percent.

Next, consider the impulse responses of sectoral price indexes to sector-specific shocks and to aggregate shocks. Fig. 1 shows the cross-section of the normalized impulse responses of sectoral price indexes to sector-specific shocks (top panel) and to aggregate shocks (bottom panel). Each panel shows the posterior density taking into account both variation across sectors and parameter uncertainty. Specifically, for each sector, 7500 draws are made from the posterior density of the normalized impulse response of the sectoral price index to a given shock.[9] Afterwards, 1000 draws are selected at random. Since there are 79 sectors, this procedure gives a sample of 79,000 impulse responses. Each panel in Fig. 1 is based on 79,000 impulse responses. The median impulse response of a sectoral price index to a sector-specific shock has the

[8] The out-of-sample forecast exercise consisted of the following steps. (1) For each specification of the dynamic factor model and for each sector: (i) compute the forecast of the normalized sectoral inflation rate one-step-ahead in the last 24 periods in the dataset and (ii) save the average root mean squared error of the 24 forecasts. (2) Perform the same exercise using an AR model for the normalized sectoral inflation rate. The AR model was estimated separately for each sector by OLS, with the number of lags equal to, alternatively, 6 and 12.

[9] See Appendix A available on Science Direct for details of the Gibbs sampler.

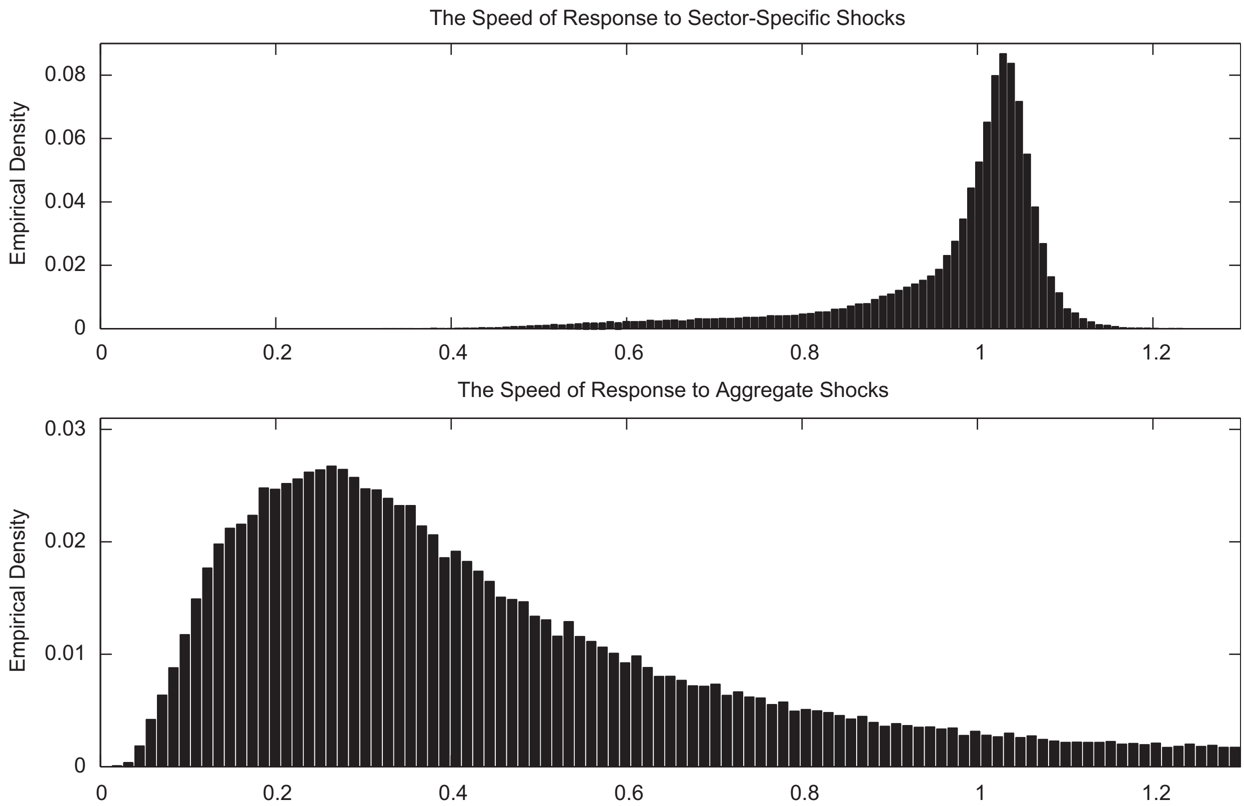


**Fig. 2.** The cross-section of the speed of response of sectoral price indexes to shocks. *Note*: This figure shows the posterior density of the speed of response of sectoral price indexes to sector-specific shocks (top panel) and to aggregate shocks (bottom panel). The posterior density takes into account variation across sectors and parameter uncertainty. The speed of response is defined in Section 4.

following shape. After a sector-specific shock, 100 percent of the long-run response of the sectoral price index occurs in the month of the shock, and the response equals the long-run response in all months following the shock. The median impulse response of a sectoral price index to an aggregate shock has a very different shape. After an aggregate shock, only 15 percent of the long-run response of the sectoral price index occurs in the month of the shock, and the response gradually approaches the long-run response in the months following the shock. Another way of summarizing the median impulse responses is as follows. The sector-specific component of the sectoral inflation rate is essentially a white noise process, while the aggregate component of the sectoral inflation rate is positively autocorrelated with an autocorrelation coefficient equal to 0.35.[10]

It is useful to compute a simple measure of the speed of the response of a price index to a given type of shock. Specifically, consider the absolute response to the shock in the short run divided by the absolute response to the shock in the long run. Take the short run to be between the impact of the shock and five months after the impact of the shock. Take the long run to be between 19 months and 24 months after the impact of the shock. Formally, let $\beta_{nm}$ denote the impulse response of the price index for sector $n$ to a sector-specific shock $m$ periods after the shock. The speed of response of the price index for sector $n$ to sector-specific shocks is defined as

$$\Lambda_n^S \equiv \frac{\frac{1}{6}\sum_{m=0}^{5}|\beta_{nm}|}{\frac{1}{6}\sum_{m=19}^{24}|\beta_{nm}|}.$$

Furthermore, let $\alpha_{nm}$ denote the impulse response of the price index for sector $n$ to an aggregate shock $m$ periods after the shock. The speed of response of the price index for sector $n$ to aggregate shocks is defined as

$$\Lambda_n^A \equiv \frac{\frac{1}{6}\sum_{m=0}^{5}|\alpha_{nm}|}{\frac{1}{6}\sum_{m=19}^{24}|\alpha_{nm}|}.$$

[10] Regressing the median impulse response of a sectoral inflation rate on its own lag yields a coefficient of 0.35.

Fig. 2 shows the cross-section of $\Lambda_n^S$ (top panel) and the cross-section of $\Lambda_n^A$ (bottom panel). Each panel shows the posterior density taking into account both variations across sectors and parameter uncertainty. Fig. 2 has two main features. The median speed of response of a sectoral price index to sector-specific shocks is much larger than the median speed of response of a sectoral price index to aggregate shocks. The median speed of response of a sectoral price index to sector-specific shocks equals 1.01. The median speed of response of a sectoral price index to aggregate shocks equals 0.41.[11] Furthermore, the cross-section of the speed of response to sector-specific shocks is tight, while the cross-section of the speed of response to aggregate shocks is dispersed. Sixty-eight percent of the posterior probability mass of $\Lambda_n^S$ lies between 0.89 and 1.05, and 68 percent of the posterior probability mass of $\Lambda_n^A$ lies between 0.2 and 1.12. There is little cross-sectional variation in the speed of response to sector-specific shocks, while there is considerable cross-sectional variation in the speed of response to aggregate shocks.[12]

## 5. Regression analysis

The last section showed that there is little cross-sectional variation in the speed of response to sector-specific shocks and considerable cross-sectional variation in the speed of response to aggregate shocks. This section studies whether the cross-sectional variation in the speed of response to a given type of shock is related to sectoral characteristics that we have information on. All regressions reported below are motivated by models of price setting that are presented in more detail in Section 7.

### *5.1. The speed of response and the frequency of price changes*

A basic prediction of the Calvo model is that sectoral price indexes respond faster to shocks in sectors with a higher frequency of price changes (holding constant all other sectoral characteristics).

Bils and Klenow (2004) reported the monthly frequency of price changes for 350 categories of consumer goods and services, based on data from the BLS for the period 1995–1997. We can match 75 of our 79 sectors into the categories studied by Bils and Klenow (2004). Nakamura and Steinsson (2008) reported the monthly frequency of price changes for 270 categories of consumer goods and services, based on data from the BLS for the period 1998–2005. We can match 77 of our 79 sectors into the categories studied by Nakamura and Steinsson (2008).

The information on the speed of response of the price index for sector $n$ to a given type of shock comes from the estimated dynamic factor model. Note that we do not know the speed of response for certain. Instead, we have a posterior density of the speed of response. To account for uncertainty about the regression relationship in the regressions below, the posterior density of the regression coefficient is reported.[13]

Consider two regressions. First, consider the regression of the speed of response of the price index for sector $n$ to aggregate shocks ($\Lambda_n^A$) on the sectoral monthly frequency of price changes from Bils and Klenow (2004) and, alternatively, on the sectoral monthly frequency of regular price changes from Nakamura and Steinsson (2008).[14] The top two rows in Table 1 show that (i) the posterior median of the regression coefficient is positive, (ii) the 90 percent posterior probability interval for the regression coefficient excludes zero, and (iii) the regression results using the Bils–Klenow frequencies differ little from the regression results using the Nakamura–Steinsson frequencies.

Second, consider the regression of the speed of response of the price index for sector $n$ to sector-specific shocks ($\Lambda_n^S$) on the sectoral monthly frequency of price changes from Bils and Klenow (2004) and, alternatively, on the sectoral monthly frequency of regular price changes from Nakamura and Steinsson (2008). These results are in the bottom two rows in Table 1. With the Bils–Klenow frequencies, the regression coefficient is positive, but the regression coefficient is significantly smaller than the coefficient in the first regression. Furthermore, with the Nakamura–Steinsson frequencies of regular price changes, there is moderately strong support for a negative relationship.

### *5.2. The speed of response and the standard deviation of shocks*

In the rational-inattention model of Maćkowiak and Wiederholt (2009a), agents pay more attention to those shocks that on average cause more variation in the optimal decision. Therefore, the model predicts that sectoral price indexes respond faster to aggregate shocks in sectors with a larger standard deviation of sectoral inflation due to aggregate shocks. Similarly,

[11] One can also look at the speed of response to shocks sector by sector. In 76 of 79 sectors, the median speed of response of the sectoral price index to sector-specific shocks is larger than the median speed of response of the sectoral price index to aggregate shocks. Furthermore, one can construct, in each sector, a posterior probability interval for the speed of response to sector-specific shocks and a posterior probability interval for the speed of response to aggregate shocks. When 68 percent posterior probability intervals are constructed, in 43 of 79 sectors the posterior probability interval for the speed of response to sector-specific shocks lies strictly above the posterior probability interval for the speed of response to aggregate shocks.

[12] Alternative measures of the speed of response to shocks yielded the same conclusions.

[13] Many draws are made from the posterior density of the speed of response. For each draw, the posterior density of the regression coefficient conditional on this draw is constructed and a draw is made from this density. This procedure yields the marginal posterior density of the regression coefficient, with the speed of response integrated out. This marginal posterior density is reported.

[14] Regular price changes in Nakamura and Steinsson (2008) exclude price changes related to sales and product substitutions.

**Table 1**
The speed of response and the frequency of price changes.

| Regressand | Regressor | |
|---|---|---|
| | Sectoral monthly frequency of price changes (Bils and Klenow, 2004) | Sectoral monthly frequency of regular price changes (Nakamura and Steinsson, 2008) |
| Speed of response of a sectoral price index to aggregate shocks | **2.04**<br>(0.29, 4.76) | |
| | | **1.55**<br>(0.12, 4.52) |
| Speed of response of a sectoral price index to sector-specific shocks | **0.14**<br>(0.02, 0.28) | |
| | | −**0.09**<br>(−0.21, 0.03) |

*Note*: These are the results from regressing the speed of response of a sectoral price index on the sectoral monthly frequency of price changes. Each number in bold type is the posterior median of the regression coefficient. The bracketed numbers show the 90 percent posterior probability interval for each regression coefficient. The regressions reported here are discussed in Section 5.1. The speed of response of a sectoral price index is defined in Section 4.

**Table 2**
The speed of response and the standard deviation of shocks.

| Regressand | Regressor | |
|---|---|---|
| | Standard deviation of sectoral inflation due to aggregate shocks | Standard deviation of sectoral inflation due to sector-specific shocks |
| Speed of response of a sectoral price index to aggregate shocks | **31.42**<br>(1.71, 85.11) | |
| | **75.45**<br>(− 17.28, 251.50) 0.92 | −**25.15**<br>(−115.42, 26.49) 0.20 |
| Speed of response of a sectoral price index to sector-specific shocks | | **1.18**<br>(−0.04, 2.47) 0.94 |

*Note*: These are the results from regressing the speed of response of a sectoral price index on the standard deviation(s) of sectoral inflation due to a given type of shock (given types of shocks). Each number in bold type is the posterior median of the regression coefficient. The bracketed numbers show the 90 percent posterior probability interval for each regression coefficient. When the interval includes zero, an additional number is reported. This number is the fraction of the posterior probability mass to the right of zero. The regressions reported here are discussed in Section 5.2. The speed of response of a sectoral price index is defined in Section 4.

the model predicts that sectoral price indexes respond faster to sector-specific shocks in sectors with a larger standard deviation of sectoral inflation due to sector-specific shocks.

Consider two regressions. First, consider the regression of the speed of response of the price index for sector $n$ to aggregate shocks ($\Lambda_n^A$) on the standard deviation of sectoral inflation due to aggregate shocks. The results are in the top row in Table 2. The posterior median of the regression coefficient is positive. The 90 percent posterior probability interval excludes zero. Second, consider the regression of the speed of response of the price index for sector $n$ to sector-specific shocks ($\Lambda_n^S$) on the standard deviation of sectoral inflation due to sector-specific shocks. The results are in the bottom row in Table 2. The posterior median of the regression coefficient is again positive. This time the 90 percent posterior probability interval includes zero but only barely. As one can see from the table, 94 percent of the posterior probability mass lies to the right of zero. One can conclude that the posterior evidence provides strong support for these predictions of the model. In addition, note that the 90 percent posterior probability intervals for the two coefficients barely overlap, suggesting that there is a difference in the magnitude of the two coefficients. Section 7 shows that the rational-inattention model of Maćkowiak and Wiederholt (2009a) predicts a difference in the magnitude of the two coefficients.[15]

Section 7 also shows another prediction of the rational-inattention model of Maćkowiak and Wiederholt (2009a). When the amount of information processed by price setters in firms is given exogenously or when price setters in firms can decide

[15] In the regressions reported in Table 2 both the regressand and the regressor (the regressors) are uncertain. Many draws are made from the joint posterior density of the regressand and the regressor (the regressors). For each joint draw, the posterior density of the regression coefficient conditional on this joint draw is constructed and a draw is made from this density. This procedure yields the marginal posterior density of the regression coefficient, with the regressand and the regressor (the regressors) integrated out. This marginal posterior density is reported.

to process more information subject to a strictly convex cost function, there is a tension between attending to aggregate conditions and attending to sector-specific conditions. Under these circumstances, the model predicts that the speed of response of a sectoral price index to aggregate shocks is (i) increasing in the standard deviation of sectoral inflation due to aggregate shocks and (ii) decreasing in the standard deviation of sectoral inflation due to sector-specific shocks. The results for the corresponding regression are in the middle row in Table 2. There is moderately strong support for this prediction of the model: 92 percent of the posterior probability mass for the coefficient on the standard deviation of sectoral inflation due to aggregate shocks lies to the right of zero, and 80 percent of the posterior probability mass for the coefficient on the standard deviation of sectoral inflation due to sector-specific shocks lies to the left of zero.

### 5.3. The frequency of price changes and the standard deviation of shocks

A basic prediction of the menu cost model is that firms change prices more frequently in sectors with larger shocks (holding constant all other sectoral characteristics).

In the data, sector-specific shocks account for a dominant share of the variance in sectoral price indexes. Therefore, a simple way to investigate this prediction of the menu cost model is to look for a positive relationship between the sectoral monthly frequency of price changes and the standard deviation of sectoral inflation due to sector-specific shocks. Table 3 shows strong evidence for the positive relationship, in the case of the Bils–Klenow frequencies and in the case of the Nakamura–Steinsson frequencies.

The menu cost model also predicts a positive relationship between the frequency of price changes and the steady-state inflation rate. This prediction was investigated, but no relationship was found between the monthly frequency of price changes in a given sector and the mean inflation rate in that sector. It is plausible that more variation in mean inflation rates than is present in this paper's sample would be needed for a significant positive relationship to arise.

## 6. Robustness

This section considers three robustness checks.

### 6.1. The distribution of sector-specific shocks

This subsection examines the posterior density of sector-specific shocks, $(v_{n1},\ldots,v_{nT})_{n=1}^{N}$, from the benchmark specification of the dynamic factor model. Specifically, the posterior density of skewness and the posterior density of kurtosis of the sector-specific shocks are examined. Each density suggests that the sector-specific shocks are slightly non-Gaussian. The posterior density of skewness has a median of zero but it has a sizable negative tail (the posterior mean is $-0.1$). The posterior density of kurtosis has a median of 3.7 and a mean of 4.2. The extent of non-Gaussianity fails to change when one allows for more lags in the sector-specific component of the sectoral inflation rate and when one adds another factor. However, the negative skewness and the excess kurtosis come mainly from only a few sectors. These sectors are dropped from the sample and the benchmark specification of the dynamic factor model is reestimated.[16] The findings reported in Sections 4 and 5 remain unaffected.[17] Furthermore, the sector-specific shocks from the reestimated benchmark specification appear approximately Gaussian. The posterior density of skewness has a median of zero and a mean of $-0.01$. The posterior density of kurtosis has a median of 3.6 and a mean of 3.7. These results suggest that the findings reported in Sections 4 and 5 are not driven by a few sectors experiencing non-Gaussian sector-specific shocks.

### 6.2. More lags and quarterly data

This subsection examines the possibility that the findings reported in Sections 4 and 5 are influenced by the fact that the sector-specific component of the sectoral inflation rate is approximated as an autoregressive process. If the sector-specific component of the sectoral inflation rate has a moving average root large in absolute value, one needs to allow for many lags in the autoregressive approximation for it to be accurate. First, a specification of the dynamic factor model is estimated that allows for more lags in the sector-specific component of the sectoral inflation rate. In particular, a specification is estimated in which the order of the polynomials $C_n(L)$ equals 12. The findings reported in Sections 4 and 5 remain unaffected. Second, the benchmark specification of the dynamic factor model is reestimated using quarterly data.[18] Not surprisingly, in the median sector the share of the variance in sectoral inflation due to sector-specific shocks falls, to 71 percent from 90 percent with monthly data. The speed of response to aggregate shocks remains unaffected. The speed of response to sector-

[16] Specifically, 11 sectors are dropped. The sample is reduced to 68 sectors.

[17] For example, the median speed of response to aggregate shocks equals 0.41, exactly as reported in Section 4. The median speed of response to sector-specific shocks equals 1.02, 0.01 higher than reported in Section 4. Sixty-eight percent of the posterior probability mass of $\Lambda_n^S$ lies between 0.89 and 1.05, exactly as reported in Section 4, and 68 percent of the posterior probability mass of $\Lambda_n^A$ lies between 0.2 and 1.05, almost exactly as reported in Section 4.

[18] The order of the polynomials $A_n(L)$ equals eight and the order of the polynomials $C_n(L)$ equals two.

**Table 3**
The frequency of price changes and the standard deviation of shocks.

| Regressand | Regressor |
|---|---|
| | Standard deviation of sectoral inflation due to sector-specific shocks |
| Sectoral monthly frequency of price changes (Bils and Klenow, 2004) | **6.09**<br>(4.62, 7.65) |
| Sectoral monthly frequency of regular price changes (Nakamura and Steinsson, 2008) | **4.61**<br>(2.53, 6.52) |

*Note*: These are the results from regressing the sectoral monthly frequency of price changes on the standard deviation of sectoral inflation due to sector-specific shocks. Each number in bold type is the posterior median of the regression coefficient. The bracketed numbers show the 90 percent posterior probability interval for each regression coefficient. The regressions reported here are discussed in Section 5.3.

**Table 4**
The speed of response and the standard deviation of shocks with quarterly data.

| Regressand | Regressor | |
|---|---|---|
| | Standard deviation of sectoral inflation due to aggregate shocks | Standard deviation of sectoral inflation due to sector-specific shocks |
| Speed of response of a sectoral price index to aggregate shocks | **29.15**<br>(6.44, 107.76) | |
| | **61.21**<br>(10.04, 297.30) | −**38.88**<br>(−221.44, 8.98) 0.09 |
| Speed of response of a sectoral price index to sector-specific shocks | | **2.19**<br>(0.70, 3.66) |

*Note*: These are the results from reestimating, based on quarterly data, the regressions reported in Table 2. Each number in bold type is the posterior median of the regression coefficient. The bracketed numbers show the 90 percent posterior probability interval for each regression coefficient. When the interval includes zero, an additional number is reported. This number is the fraction of the posterior probability mass to the right of zero. The regressions reported here are discussed in Section 6.2. The speed of response of a sectoral price index is defined in Section 4.

specific shocks falls somewhat, but it remains much higher than the speed of response to aggregate shocks. The support for the regression relationships predicted by the rational-inattention model of Maćkowiak and Wiederholt (2009a) actually strengthens. See Table 4 which reproduces, based on quarterly data, the rational-inattention model regressions from Table 2.

### *6.3. Multiple factors*

The final robustness check is to estimate a specification of the dynamic factor model with two factors. In particular, a specification is estimated in which $u_t$ follows a bivariate vector process and the order of the polynomials $C_n(L)$ equals 6. The conclusion that sector-specific shocks account for a dominant share of the variance in sectoral price indexes remains unaffected. In the median sector, the share of the variance in sectoral inflation due to sector-specific shocks falls only a little, to 89 percent from 90 percent in the benchmark specification. The conclusion that sectoral price indexes respond quickly to sector-specific shocks and slowly to aggregate shocks also remains unaffected, although the speed of response to aggregate shocks increases somewhat. In the median sector, 15 percent of the long-run response of the sectoral price index occurs within one month of an innovation in one factor; and 30 percent of the long-run response of the sectoral price index occurs within one month of an innovation in the other factor. Most regression relationships reported in Section 5 become somewhat weaker. This is as expected given that many parameters are estimated in the specification with two factors. Note also that the specification with two factors performs worse in the out-of-sample forecast exercise than the benchmark specification. This difference makes us focus on the results from the benchmark specification.

## 7. Models of price setting

This section studies whether different models of price setting can match the empirical findings reported in Sections 4–6. Four models of price setting are considered: the Calvo model, a menu cost model, the sticky-information model developed in Mankiw and Reis (2002), and the rational-inattention model developed in Maćkowiak and Wiederholt (2009a). Since several of the empirical findings reported in Sections 4–6 are about the response of sectoral price indexes to sector-specific shocks, versions of these four models with multiple sectors and sector-specific shocks are studied. To fix ideas, Section 7.1 presents a specific multi-sector setup. Later it is shown that the main theoretical results do not depend on the details of the multi-sector setup.

### 7.1. Common setup

Consider an economy with a continuum of sectors of mass one. In each sector, there is a continuum of firms of mass one. Sectors are indexed by $n$ and firms within a sector are indexed by $i$. Each firm supplies a differentiated good and sets the price for the good.

The demand for good $i$ in sector $n$ in period $t$ is given by[19]

$$C_{int} = \left(\frac{P_{int}}{P_{nt}}\right)^{-\theta}\left(\frac{P_{nt}}{P_t}\right)^{-\eta} C_t, \tag{2}$$

where $P_{int}$ is the price of good $i$ in sector $n$, $P_{nt}$ is the sectoral price index, $P_t$ is the aggregate price index and $C_t$ is aggregate composite consumption. The parameters satisfy $\theta > 1$ and $\eta > 1$. The sectoral price index and the aggregate price index are given by

$$P_{nt} = \left(\int_0^1 P_{int}^{1-\theta}\, di\right)^{1/(1-\theta)} \tag{3}$$

and

$$P_t = \left(\int_0^1 P_{nt}^{1-\eta}\, dn\right)^{1/(1-\eta)}. \tag{4}$$

Output of firm $i$ in sector $n$ in period $t$ is given by

$$Y_{int} = Z_{nt} L_{int}^{\alpha}, \tag{5}$$

where $Z_{nt}$ is sector-specific total factor productivity (TFP) and $L_{int}$ is labor input of the firm. The parameter $\alpha \in (0,\ 1]$ is the elasticity of output with respect to labor input. In every period, firms produce the output that is required to satisfy demand

$$Y_{int} = C_{int}. \tag{6}$$

Finally, the real wage rate in period $t$ is assumed to equal $w(C_t)$, where $w : \mathbb{R}_+ \to \mathbb{R}_+$ is a strictly increasing, twice continuously differentiable function.

Substituting the demand function (2), the production function (5), Eq. (6) and the real wage rate $w(C_t)$ into the usual expression for nominal profits and dividing by the price level yields the real profit function. A log-quadratic approximation of the real profit function around the non-stochastic solution of the model yields the following expression for the profit-maximizing price in period $t$:

$$p_{int}^{\diamond} = \underbrace{p_t + \frac{\omega + \frac{1-\alpha}{\alpha}}{1 + \frac{1-\alpha}{\alpha}\theta} c_t + \frac{\frac{1-\alpha}{\alpha}(\theta - \eta)}{1 + \frac{1-\alpha}{\alpha}\theta} \hat{p}_{nt}^{A}}_{p_{int}^{\diamond A}} + \underbrace{\frac{\frac{1-\alpha}{\alpha}(\theta - \eta)}{1 + \frac{1-\alpha}{\alpha}\theta} \hat{p}_{nt}^{S} - \frac{\frac{1}{\alpha}}{1 + \frac{1-\alpha}{\alpha}\theta} z_{nt}}_{p_{int}^{\diamond S}}, \tag{7}$$

where $p_{int} = \ln(P_{int})$, $p_t = \ln(P_t)$, $c_t = \ln(C_t/\bar{C})$, $\hat{p}_{nt} = \ln(P_{nt}/P_t)$, and $z_{nt} = \ln(Z_{nt}/\bar{Z})$. Furthermore, $\hat{p}_{nt}^{A}$ is the component of $\hat{p}_{nt}$ driven by aggregate shocks and $\hat{p}_{nt}^{S}$ is the component of $\hat{p}_{nt}$ driven by sector-specific shocks. Here $\bar{C}$, $\bar{Z}$ and $\omega$ denote composite consumption, TFP and the elasticity of the real wage with respect to composite consumption at the non-stochastic solution. Note that the profit-maximizing price has an aggregate component, $p_{int}^{\diamond A}$, and a sector-specific component, $p_{int}^{\diamond S}$.[20] Furthermore, after the log-quadratic approximation of the real profit function, the profit loss in period $t$ due to a deviation from the profit-maximizing price equals

$$\frac{\bar{C}(\theta - 1)\left(1 + \frac{1-\alpha}{\alpha}\theta\right)}{2}(p_{int} - p_{int}^{\diamond})^2. \tag{8}$$

See Appendix A in Maćkowiak and Wiederholt (2009a) for the derivation of Eq. (8).

In addition to the log-quadratic approximation of the real profit function, log-linearization of the equations for the price indexes around the non-stochastic solution of the model yields

$$p_{nt} = \int_0^1 p_{int}\, di \tag{9}$$

[19] The demand function (2) with price indexes (3) and (4) can be derived from expenditure minimization by households when households have a CES consumption aggregator, where $\theta > 1$ is the elasticity of substitution between goods from the same sector and $\eta > 1$ is the elasticity of substitution between consumption aggregates from different sectors.

[20] Introducing sector-specific shocks in the form of multiplicative demand shocks in (2) instead of multiplicative productivity shocks in (5) yields an equation for the profit-maximizing price that is almost identical to Eq. (7). The only difference is the coefficient in front of $z_{nt}$.

and

$$p_t = \int_0^1 p_{nt}\, dn, \tag{10}$$

where $p_{nt} = \ln(P_{nt})$.

In the following price-setting models, it is assumed that the profit-maximizing price equals (7), the profit loss due to a deviation from the profit-maximizing price equals (8), and the sectoral price index and the aggregate price index are given by Eqs. (9) and (10), respectively.

### 7.2. Calvo model

In the Calvo model, a firm can adjust its price with a constant probability in any given period. Let $\lambda_n$ denote the probability that a firm in sector $n$ can adjust its price. Assume that the profit-maximizing price of good $i$ in sector $n$ in period $t$ is given by Eq. (7), the price index for sector $n$ in period $t$ is given by Eq. (9), and a firm in sector $n$ that can adjust its price in period $t$ sets the price that minimizes

$$E_t\left[\sum_{s=t}^{\infty}[(1-\lambda_n)\beta]^{s-t}\frac{\bar{C}(\theta-1)\left(1+\dfrac{1-\alpha}{\alpha}\theta\right)}{2}(p_{int}-p_{ins}^{\diamond})^2\right]. \tag{11}$$

In this model, the profit-maximizing price equals the sum of two components: an aggregate component and a sector-specific component. Furthermore, the aggregate component, $p_{int}^{\diamond A}$, and the sector-specific component, $p_{int}^{\diamond S}$, are the same for all firms within a sector. Formally, the profit-maximizing price of firm $i$ in sector $n$ in period $t$ has the form

$$p_{int}^{\diamond} = p_{nt}^{\diamond A} + p_{nt}^{\diamond S}. \tag{12}$$

A firm in sector $n$ that can adjust its price in period $t$ sets the price

$$p_{int}^{*} = [1-(1-\lambda_n)\beta]E_t\left[\sum_{s=t}^{\infty}[(1-\lambda_n)\beta]^{s-t}p_{ins}^{\diamond}\right]. \tag{13}$$

The price set by adjusting firms equals a weighted average of the current profit-maximizing price and future profit-maximizing prices. Finally, the price index for sector $n$ in period $t$ equals

$$p_{nt} = (1-\lambda_n)p_{nt-1} + \lambda_n p_{int}^{*}, \tag{14}$$

because the adjusting firms are drawn randomly and all adjusting firms in a sector set the same price.

Recall that the median impulse response of sectoral price indexes to sector-specific shocks reported in Fig. 1 has the property that all of the response of the sectoral price index to a sector-specific shock occurs in the month of the shock. The following proposition answers the question of whether the standard Calvo model can match the median impulse response of sectoral price indexes to sector-specific shocks.

**Proposition 1** (*Calvo model with sector-specific shocks*). *Suppose that the profit-maximizing price of firm i in sector n in period t is given by Eq.* (12), *the price set by adjusting firms is given by Eq.* (13), *and the sectoral price index is given by Eq.* (14). *Then, the impulse response of the price index for sector n to a shock equals x on impact of the shock and in all periods following the shock if and only if the impulse response of the profit-maximizing price to the shock equals* (i)

$$\frac{\dfrac{1}{\lambda_n}-(1-\lambda_n)\beta}{1-(1-\lambda_n)\beta}x, \tag{15}$$

*on impact of the shock and* (ii) *x thereafter.*

**Proof.** See Appendix B available on Science Direct.

In the Calvo model, there exists a unique impulse response of the profit-maximizing price to a sector-specific shock which implies that all of the response of the sectoral price index to the sector-specific shock occurs in the period of the shock. If prices are flexible ($\lambda_n = 1$), the sector-specific component of the profit-maximizing price has to follow a random walk. If prices are sticky ($0<\lambda_n<1$), the profit-maximizing price first needs to jump by expression (15) on impact of the shock and then has to jump back to $x$ in the period following the shock to generate a response equal to $x$ of the sectoral price index on impact of the shock and in all periods following the shock. Proposition 1 follows directly from Eqs. (12)–(14). Note that the required extent of overshooting of the profit-maximizing price depends only on the two parameters $\lambda_n$ and $\beta$.

To illustrate Proposition 1, consider the following three examples. In each example, one period equals one month. Therefore, set $\beta = 0.99^{1/3}$. First, suppose that $\lambda_n = (1/12)$. This value implies that firms adjust their prices on average once a year. Then the profit-maximizing response on impact has to overshoot the profit-maximizing response in the next month by a *factor* of 128. Second, suppose that $\lambda_n = 0.087$. This is the monthly frequency of regular price changes (i.e. excluding

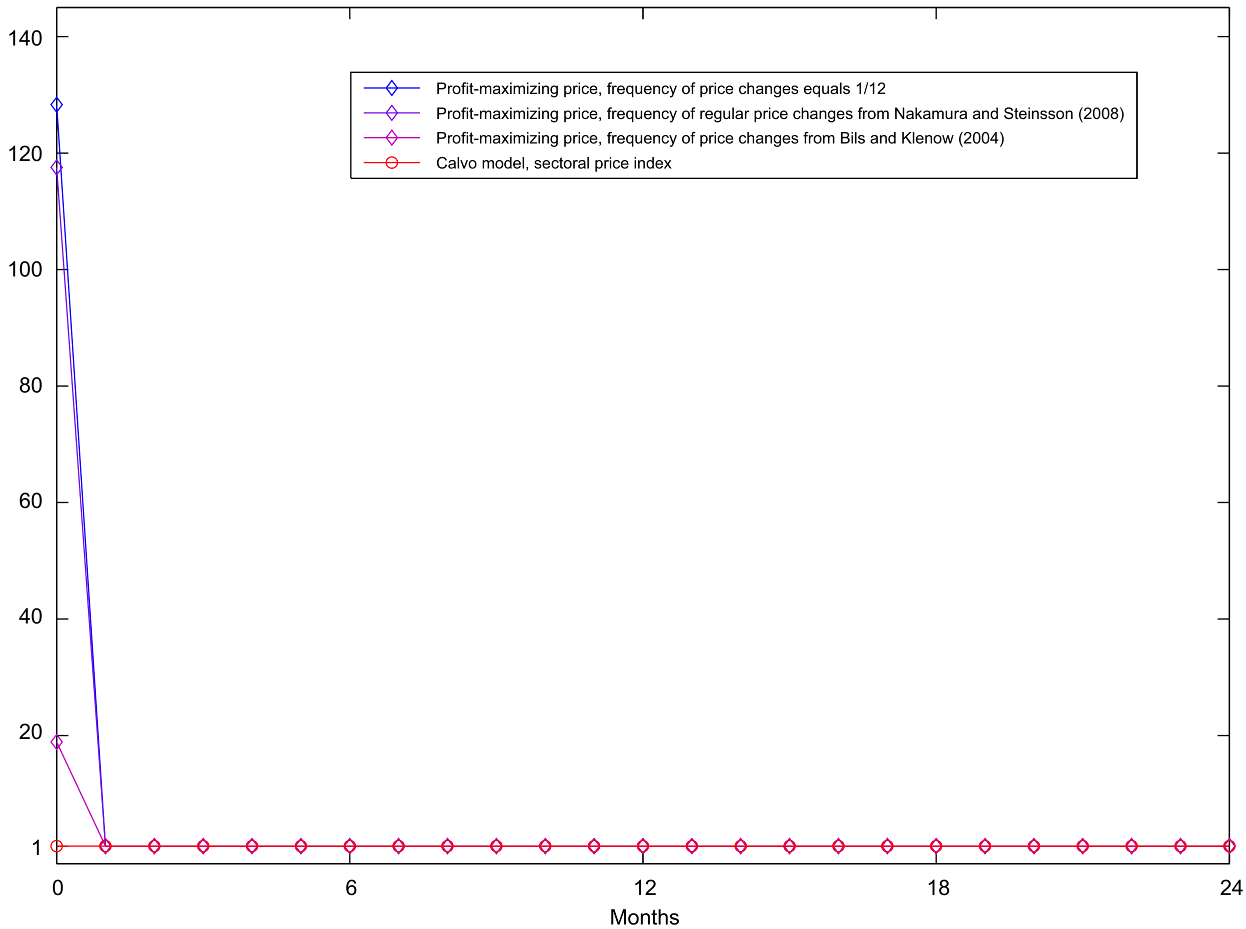


**Fig. 3.** Impulse responses to sector-specific shocks: profit-maximizing price and sectoral price index in the Calvo model. *Note*: This figure shows the impulse response of the profit-maximizing price to a sector-specific shock (under three different assumptions concerning the frequency of price changes) and the impulse response of the sectoral price index in the Calvo model to the same shock (this impulse response is normalized to one).

sales and item substitutions) reported by Nakamura and Steinsson (2008). Then the profit-maximizing response on impact has to overshoot the profit-maximizing response in the next month by a factor of 118. Third, suppose that $\lambda_n = 0.21$. This is the monthly frequency of price changes reported by Bils and Klenow (2004). Then the profit-maximizing response on impact has to overshoot the profit-maximizing response in the next month by a factor of 19. All three examples are depicted in Fig. 3. For the sake of clarity, the impulse response of the sectoral price index in Fig. 3 is normalized to one.

Going a step further, consider the impulse response of sector-specific productivity that yields the impulse response of the profit-maximizing price described in Proposition 1. When the profit-maximizing price is given by Eq. (7), the sector-specific component of the profit-maximizing price equals

$$p_{nt}^{\diamond S} = \frac{\frac{1-\alpha}{\alpha}(\theta-\eta)}{1+\frac{1-\alpha}{\alpha}\theta}\hat{p}_{nt}^{S} - \frac{\frac{1}{\alpha}}{1+\frac{1-\alpha}{\alpha}\theta}z_{nt}. \tag{16}$$

Solving the last equation for sector-specific productivity yields

$$z_{nt} = -\frac{1+\frac{1-\alpha}{\alpha}\theta}{\frac{1}{\alpha}}\left[p_{nt}^{\diamond S} - \frac{\frac{1-\alpha}{\alpha}(\theta-\eta)}{1+\frac{1-\alpha}{\alpha}\theta}\hat{p}_{nt}^{S}\right]. \tag{17}$$

Substituting the impulse response of the profit-maximizing price described in Proposition 1 and the impulse response of the sectoral price index into Eq. (17) delivers the impulse response of sector-specific productivity that yields the impulse response of the profit-maximizing price described in Proposition 1. For the parameter values $\alpha = (2/3)$, $\theta = 4$ and $\eta = 2$, Fig. 4 shows the impulse responses of sector-specific productivity that yield the impulse responses of the profit-maximizing price depicted in Fig. 3.

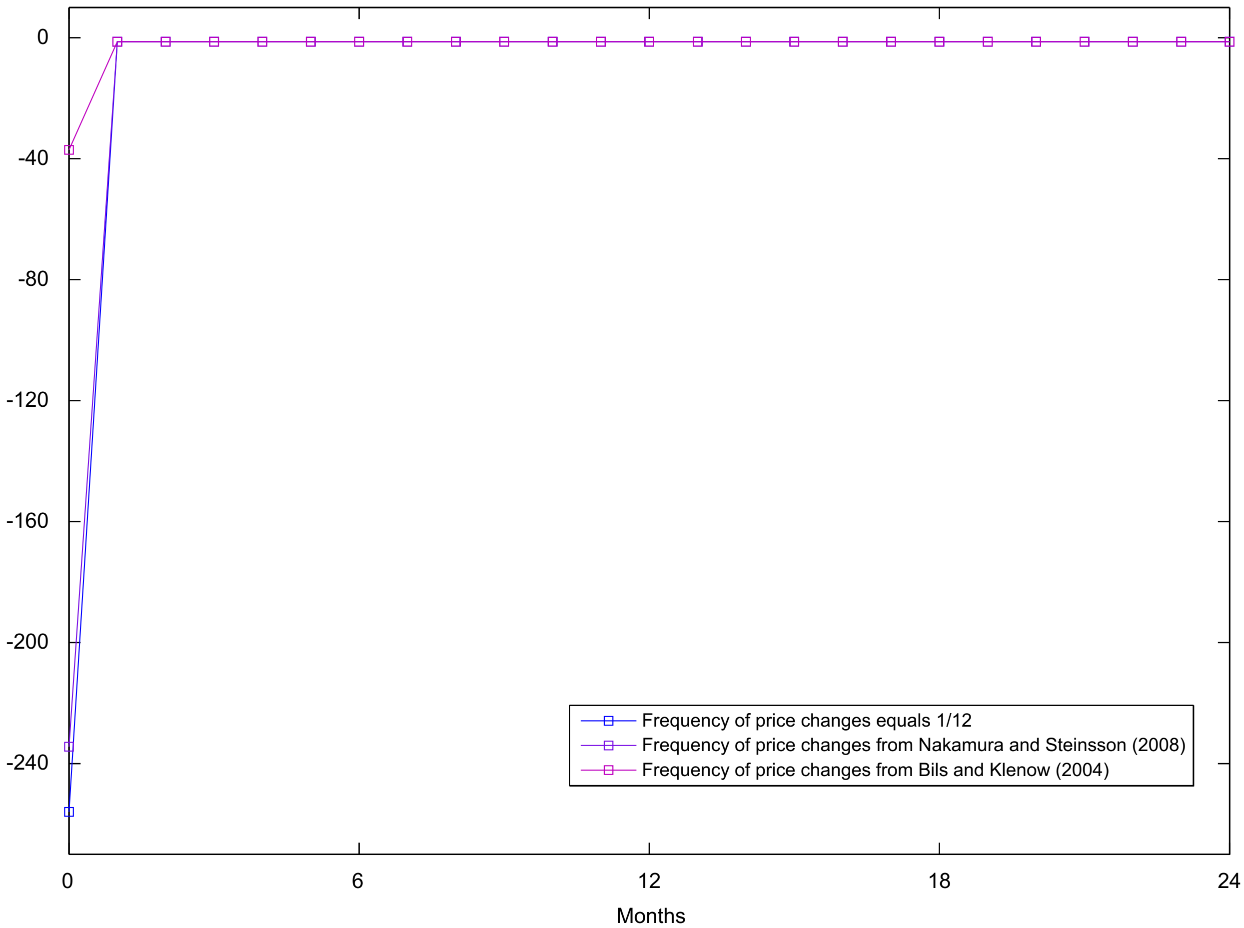


**Fig. 4.** Impulse responses of sector-specific productivity that yield the profit-maximizing impulse responses in Fig. 3. *Note*: This figure shows the impulse responses of sector-specific productivity to an own shock (under three different assumptions concerning the frequency of price changes) that yield the impulse responses of the profit-maximizing price depicted in Fig. 3.

We interpret the results presented in Fig. 1, Proposition 1 and Fig. 3 as saying that the standard Calvo model has difficulties matching the median empirical response of sectoral price indexes to sector-specific shocks. To match the median empirical response of sectoral price indexes to sector-specific shocks, one needs a value for the Calvo parameter that is close to one in a monthly model or one has to make an extreme assumption concerning the response of the profit-maximizing price to sector-specific shocks. One could try to modify the Calvo model. Since Proposition 1 follows directly from Eqs. (12)–(14), one has to modify at least one of these three equations to change this property of the model. Consider two potential modifications. First, one could assume that the profit-maximizing price differs across firms within a sector. However, the only change in Proposition 1 is that the proposition becomes a statement about the response of the average profit-maximizing price in the sector. For some firms the profit-maximizing price can respond less but then for other firms the profit-maximizing price has to respond more. Second, one could assume that with probability $\lambda_n^A$ a firm can adjust *only* the aggregate component of its price and with probability $\lambda_n^S$ a firm can adjust *only* the sector-specific component of its price. If one assumes in addition that the parameter $\lambda_n^A$ is small and the parameter $\lambda_n^S$ is large, the model can generate a slow response of the sectoral price index to aggregate shocks and a quick response of the sectoral price index to sector-specific shocks. However, it seems difficult to justify these assumptions in the context of the Calvo model.

Next, consider whether the standard Calvo model can match the cross-sectional distribution of the speed of response to sector-specific shocks. First, consider the case: $\theta = \eta$ and $z_{nt}$ following a random walk. In this case, the sector-specific component of the profit-maximizing price (7) is independent of the prices set by other firms and follows a random walk. The impulse response of the price index for sector $n$ to a sector-specific shock then has the property that the fraction of the long-run response that has occurred, say, three periods after the shock simply equals the fraction of firms that have adjusted their prices in the last four periods:

$$\sum_{j=0}^{3} \lambda_n (1-\lambda_n)^j = 1-(1-\lambda_n)^4. \tag{18}$$

For $\lambda_n = 0.1$, 0.25 and 0.5, expression (18) equals 0.34, 0.68 and 0.94, respectively. Furthermore, according to Table A1 in Bils and Klenow (2004), these three values for $\lambda_n$ correspond roughly to the 1st decile, the median and the 9th decile of the cross-sectional distribution of the monthly frequency of price changes in our sample of sectors. Hence, expression (18) and the cross-sectional distribution of the frequency of price changes imply substantial cross-sectional variation in the speed of response to sector-specific shocks. By contrast, the empirical part of this paper finds little cross-sectional variation in the speed of response to sector-specific shocks. See Fig. 2. Expression (18) is derived assuming that $\theta = \eta$. When $\theta > \eta$, there is strategic complementarity in pricing in response to sector-specific shocks, which amplifies cross-sectoral differences in $\lambda_n$. By contrast, when $\theta < \eta$, there is strategic substitutability in pricing in response to sector-specific shocks, which mutes cross-sectoral differences in $\lambda_n$. Hence, to reduce the cross-sectional variation in the speed of response to sector-specific shocks in the standard Calvo model, one could assume $\theta < \eta$. However, this assumption seems implausible because $\theta < \eta$ means that the elasticity of substitution within sectors is smaller than the elasticity of substitution across sectors. Expression (18) is also based on the assumption that $z_{nt}$ follows a random walk. Thus, the other possibility of reducing the cross-sectional variation in the speed of response to sector-specific shocks in the standard Calvo model is to assume a different $z_{nt}$ process. If sector-specific productivity "overshoots" on impact of a sector-specific shock and the extent of "overshooting" is larger in sectors with a smaller frequency of price changes, then there is less cross-sectional variation in the speed of response to sector-specific shocks. In fact, if in all sectors the impulse response of the profit-maximizing price to a sector-specific shock equals the one described in Proposition 1, then all sectoral price indexes respond fully on impact to sector-specific shocks and there is nocross-sectional variation in the speed of response to sector-specific shocks. However, this requires a very specific variation of the extent of "overshooting" with the frequency of price changes. For example, according to Eq. (15), the extent of "overshooting" in a sector with $\lambda_n = 0.1$ has to equal 30 times the extent of "overshooting" in a sector with $\lambda_n = 0.5$.

### 7.3. Sticky-information model

In the sticky-information model developed in Mankiw and Reis (2002), a firm can update its pricing plan with a constant probability in any given period. A pricing plan specifies a price path (i.e. a price as a function of time). The difference with the Calvo model is that firms choose a price path instead of a price. To understand the implications of this model for the impulse responses of sectoral price indexes to aggregate shocks and to sector-specific shocks consider a multi-sector version of the model with sector-specific shocks.

Let $\lambda_n$ denote the probability that a firm in sector $n$ can update its pricing plan. Assume that the profit-maximizing price of good $i$ in sector $n$ in period $t$ is given by Eq. (7), the price index for sector $n$ in period $t$ is given by Eq. (9), and a firm in sector $n$ that can update its pricing plan in period $t$ chooses the price path that minimizes

$$E_t\left[\sum_{s=t}^{\infty}\beta^{s-t}\frac{\bar{C}(\theta-1)\left(1+\frac{1-\alpha}{\alpha}\theta\right)}{2}(p_{ins}-p_{ins}^{\diamond})^2\right]. \tag{19}$$

In this model, the profit-maximizing price of firm $i$ in sector $n$ in period $t$ has the form

$$p_{int}^{\diamond} = p_{nt}^{\diamond A} + p_{nt}^{\diamond S}, \tag{20}$$

a firm that can update its pricing plan in period $t$ chooses a price for period $s \geq t$ that equals the conditional expectation of the profit-maximizing price in period $s$

$$p_{ins|t} = E_t[p_{ins}^{\diamond}], \tag{21}$$

and the price index for sector $n$ in period $t$ equals

$$p_{nt} = \sum_{j=0}^{\infty}\lambda_n(1-\lambda_n)^j E_{t-j}[p_{int}^{\diamond}], \tag{22}$$

because a fraction $\lambda_n(1-\lambda_n)^j$ of firms in sector $n$ last updated their pricing plans $j$ periods ago and these firms set a price equal to $E_{t-j}[p_{int}^{\diamond}]$.

Comparing Eqs. (13) and (14) and Eqs. (21) and (22) shows two differences between the Calvo model and the sticky-information model. First, in the Calvo model firms front-load expected future changes in the profit-maximizing price, while in the sticky-information model firms wait with the price adjustment until the expected change in the profit-maximizing price actually occurs. Second, in the Calvo model inflation (i.e. a change in the price level) only comes from the fraction $\lambda_n$ of firms that can adjust their prices in the current period, while in the sticky-information model inflation may also come from the fraction $(1-\lambda_n)$ of firms that cannot update their pricing plans in the current period. Mankiw and Reis (2002) showed that these two differences have interesting implications for the response of inflation and output to nominal shocks and to (anticipated and unanticipated) disinflations.[21]

[21] These statements refer to the Calvo model without indexation. The Calvo model with indexation to past inflation is more similar to the sticky-information model because in the Calvo model with indexation by setting a price the firm effectively chooses a price path.

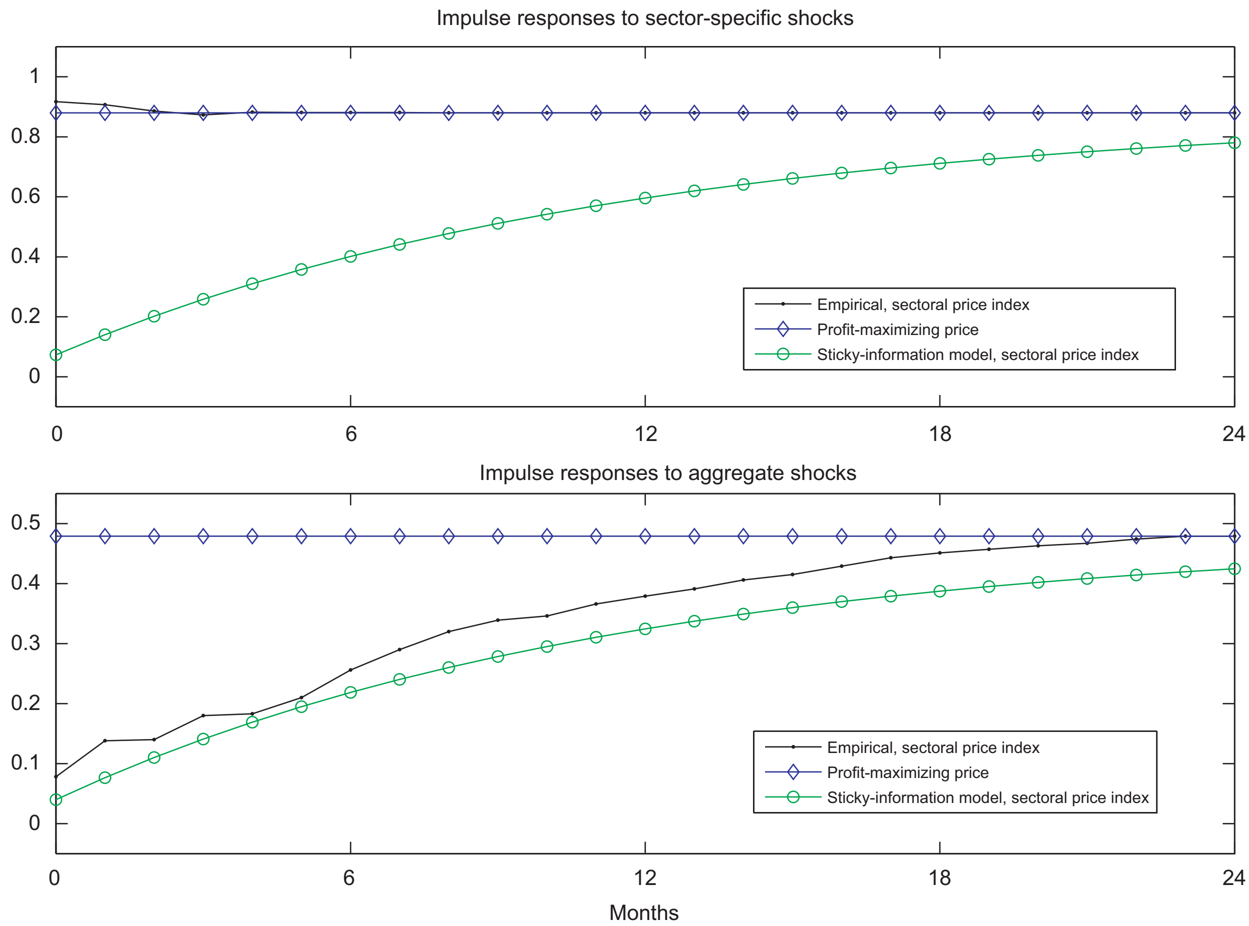


**Fig. 5.** Impulse responses: empirical, profit-maximizing, and sticky-information. *Note*: This figure shows the impulse responses to sector-specific shocks (top panel) and to aggregate shocks (bottom panel) of three objects: (i) the sectoral price index in the data (the medians from Fig. 1), (ii) the profit-maximizing price, and (iii) the sectoral price index in the sticky-information model.

To understand the implications of the standard sticky-information model for the impulse responses of sectoral price indexes to aggregate shocks and to sector-specific shocks, note the following property of impulse response functions in the standard sticky-information model. Firms that have updated their pricing plans since a shock occurred respond perfectly to the shock. All other firms do not respond at all to the shock. Furthermore, the fraction of firms that have updated their pricing plans over the last $\tau$ periods in sector $n$ equals

$$\sum_{j=0}^{\tau} \lambda_n (1-\lambda_n)^j = 1-(1-\lambda_n)^{\tau+1}. \tag{23}$$

Thus, the response of the price index for sector $n$ in period $t$ to a shock that occurred $\tau$ periods ago simply equals $[1-(1-\lambda_n)^{\tau+1}]$ times the response of the profit-maximizing price in sector $n$ in period $t$ to the same shock. This is true for any shock.

To illustrate this result, consider the following example. Suppose that in sector $n$ the aggregate component of the profit-maximizing price follows a random walk with a standard deviation of the innovation equal to $\sigma_A$ and the sector-specific component of the profit-maximizing price follows a random walk with a standard deviation of the innovation equal to $\sigma_S$. Furthermore, suppose that firms in sector $n$ update their pricing plans on average once a year, as assumed in Mankiw and Reis (2002). In a monthly model, this means $\lambda_n = (1/12)$. Fig. 5 shows the impulse responses of the sectoral price index to aggregate shocks and to sector-specific shocks implied by the model for $\sigma_A = 0.48$ and $\sigma_S = 0.88$.[22] The impulse responses of the sectoral price index to the two shocks have an identical shape, independent of the standard deviation of the two shocks. The reason is that the impulse responses of the profit-maximizing price to the two shocks have an identical shape.

[22] The median impulse response of a sectoral price index to aggregate shocks reported in Fig. 1 equals 0.48 in the long run. The median impulse response of a sectoral price index to sector-specific shocks reported in Fig. 1 equals 0.88 in the long run.

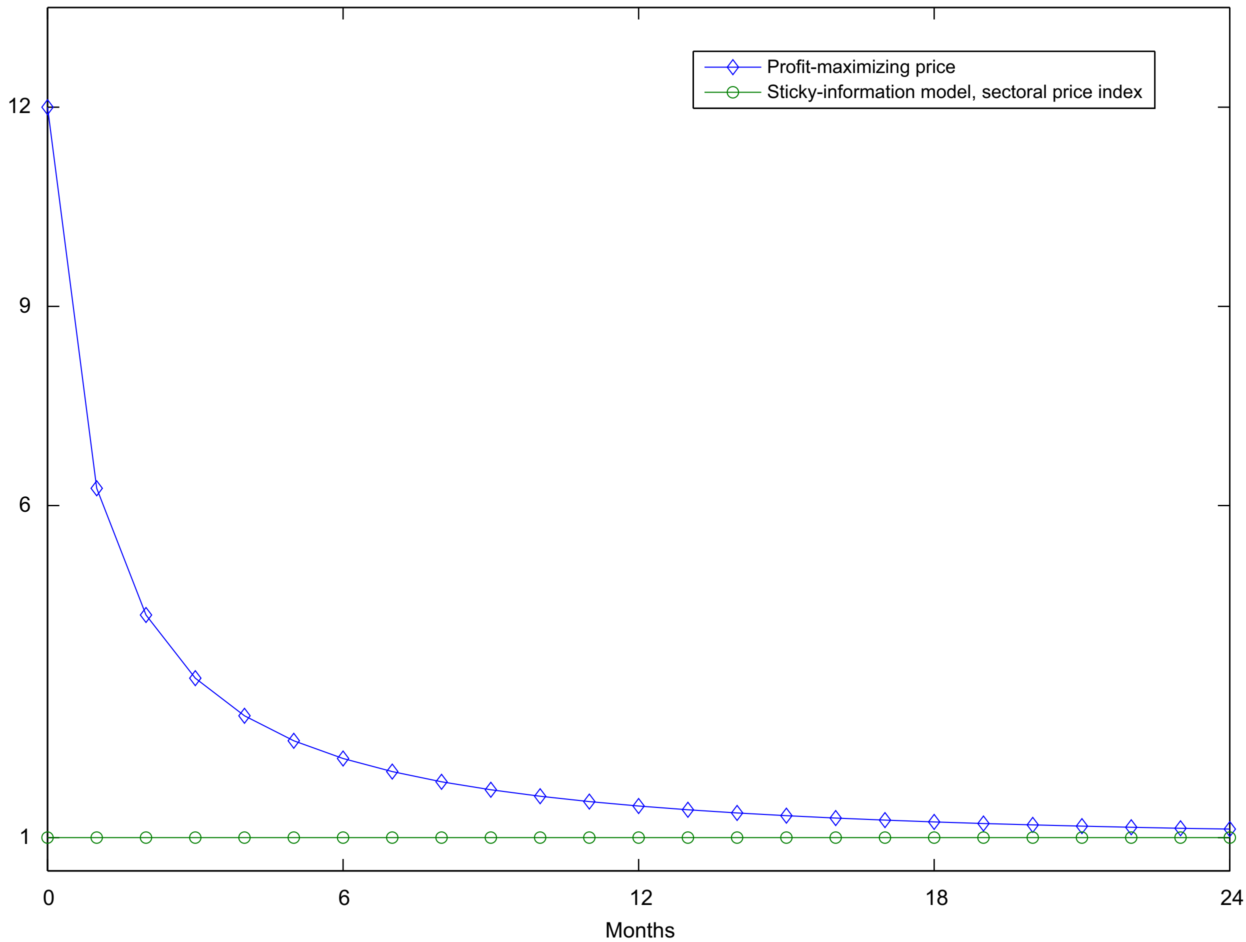


**Fig. 6.** Impulse responses to sector-specific shocks: profit-maximizing price and sectoral price index in the sticky-information model. *Note*: This figure shows the impulse response of the profit-maximizing price to a sector-specific shock (assuming updating of pricing plans once a year) and the impulse response of the sectoral price index in the sticky-information model to the same shock (this impulse response is normalized to one).

For comparison, Fig. 5 also reproduces from Fig. 1 the median empirical response of sectoral price indexes to aggregate shocks as well as the median empirical response of sectoral price indexes to sector-specific shocks.

The following proposition answers the question of whether the standard sticky-information model can match the median impulse response of sectoral price indexes to sector-specific shocks reported in Fig. 1.

**Proposition 2** (*Sticky-information model with sector-specific shocks*). *Suppose that the profit-maximizing price of firm i in sector n in period t is given by Eq.* (20) *and the sectoral price index is given by Eq.* (22). *Then, the impulse response of the price index for sector n to a shock equals x on impact of the shock and in all periods following the shock if and only if, for all* $\tau = 0, 1, 2, \ldots$, *the impulse response of the profit-maximizing price* $\tau$ *periods after the shock equals*

$$\frac{1}{1-(1-\lambda_n)^{\tau+1}}x. \tag{24}$$

**Proof.** This result follows directly from the sentence below Eq. (23). □

In the standard sticky-information model, there exists a unique impulse response of the profit-maximizing price to a sector-specific shock which implies that all of the response of the sectoral price index to a sector-specific shock occurs in the period of the shock. If firms update their pricing plans every period ($\lambda_n = 1$), the sector-specific component of the profit-maximizing price has to follow a random walk. If firms update their pricing plans infrequently ($0 < \lambda_n < 1$), the profit-maximizing price first needs to jump by $(1/\lambda_n)x$ in the period of the shock and then has to decay slowly to $x$ in the periods following the shock to generate a response equal to $x$ of the sectoral price index on impact of the shock and in all periods following the shock. Proposition 2 follows directly from Eqs. (20) and (22). Note that the required extent of overshooting of the profit-maximizing price depends only on the parameter $\lambda_n$.

To illustrate Proposition 2, consider the following example. Suppose that firms update their pricing plans on average once a year, as assumed in Mankiw and Reis (2002). In a monthly model, this means $\lambda_n = (1/12)$. Then the profit-maximizing response on impact of a sector-specific shock has to overshoot the profit-maximizing response in the long run by a *factor* of 12. See Fig. 6. Again one can compute from Eq. (17) the impulse response of sector-specific productivity that yields this impulse response of the profit-maximizing price. Note that less overshooting is necessary in the sticky-information model than in the Calvo model for the same value of $\lambda_n$, but the extent of overshooting is still large.

We interpret the results presented in Fig. 5, Proposition 2 and Fig. 6 as saying that the standard sticky-information model has difficulties matching the median empirical response of sectoral price indexes to sector-specific shocks. To match the median empirical response of sectoral price indexes to sector-specific shocks, one needs a value for $\lambda_n$ close to one in a monthly model or one has to make an extreme assumption about the response of the profit-maximizing price to sector-specific shocks. One could modify the sticky-information model. Since Proposition 2 follows directly from Eqs. (20) and (22), one has to modify at least one of these two equations to change this property of the model. Consider two potential modifications. First, one could assume that the profit-maximizing price differs across firms within a sector. The only change in Proposition 2 is that the proposition becomes a statement about the response of the average profit-maximizing price in the sector. Second, one could assume that with probability $\lambda_n^A$ a firm updates only its information concerning aggregate conditions and with probability $\lambda_n^S$ a firm updates only its information concerning sector-specific conditions. If one assumes in addition that the parameter $\lambda_n^A$ is small and the parameter $\lambda_n^S$ is large, the model can generate a slow response of the sectoral price index to aggregate shocks and a quick response of the sectoral price index to sector-specific shocks. These assumptions seem plausible in the context of the sticky-information model. In particular, Reis (2006) showed that a model with a fixed cost of obtaining perfect information can provide a microfoundation for the sticky-information model of Mankiw and Reis (2002). One could envision a modification of the Reis (2006) model with the property that there is one fixed cost of obtaining perfect information concerning aggregate conditions and another fixed cost of obtaining perfect information concerning sector-specific conditions. This would make the model more similar to the model presented in the next paragraph.

### 7.4. Rational-inattention model of Maćkowiak and Wiederholt (2009a)

In the rational-inattention model developed in Maćkowiak and Wiederholt (2009a), price setters in firms have limited attention and decide what to focus on. Price setters face a trade-off between paying attention to aggregate conditions and paying attention to idiosyncratic conditions. Following Sims (2003), limited attention is modeled as a constraint on information flow. To understand the implications of this model for the impulse responses of sectoral price indexes to aggregate shocks and to sector-specific shocks, consider a simple multi-sector version of this model with sector-specific shocks.

The profit-maximizing price of good $i$ in sector $n$ in period $t$ is given by Eq. (7). In period zero, the decision-maker in a firm chooses the precision of the signals that he or she will receive in the following periods. In each period $t \geq 1$, the decision-maker receives the signals and sets a price equal to the conditional expectation of the profit-maximizing price. In each period $t \geq 1$, the expectation is formed given the sequence of all signals that the decision-maker has received up to that point in time. The sectoral price index for sector $n$ in period $t$ is given by Eq. (9).

To make the results for this model as transparent as possible, this subsection presents an analytical solution for the price index for sector $n$ in the case when the aggregate component and the sector-specific component of the profit-maximizing price each follow a Gaussian random walk. It is straightforward to compute numerical solutions of the model when the profit-maximizing price follows some other Gaussian process.[23]

Formally, in period zero, the decision-maker in a firm chooses the precision of the signals so as to minimize the expected discounted sum of losses in profits due to deviations of the actual price from the profit-maximizing price:

$$\min_{(\sigma_\varepsilon,\sigma_\psi)\in\mathscr{R}_+^2} E\left[\sum_{t=1}^{\infty}\beta^t \frac{\bar{C}(\theta-1)\left(1+\frac{1-\alpha}{\alpha}\theta\right)}{2}(p_{int}-p_{int}^{\diamond})^2\right], \tag{25}$$

subject to (i) the process for the profit-maximizing price

$$p_{int}^{\diamond} = p_{int}^{\diamond A} + p_{int}^{\diamond S} \tag{26}$$

with

$$p_{int}^{\diamond A} = p_{int-1}^{\diamond A} + \sigma_A u_t \tag{27}$$

and

$$p_{int}^{\diamond S} = p_{int-1}^{\diamond S} + \sigma_S \nu_{nt}, \tag{28}$$

[23] See Maćkowiak and Wiederholt (2009a, b).

where $u_t$ and $\nu_{nt}$ follow independent, unit-variance Gaussian white noise processes; (ii) the optimal price setting decision in period $t$ given information in period $t$

$$p_{int} = E[p^{\diamond}_{int}|s^t_{in}], \tag{29}$$

where $s^t_{in} = (s^0_{in}, s_{in1}, s_{in2}, \ldots, s_{int})$ is the sequence of all signals that the decision-maker in firm $i$ in sector $n$ has received up to and including period $t$; (iii) an assumption concerning the set of signal vectors that the decision-maker can choose from

$$s_{int} = \begin{pmatrix} s^A_{int} \\ s^S_{int} \end{pmatrix} = \begin{pmatrix} p^{\diamond A}_{int} \\ p^{\diamond S}_{int} \end{pmatrix} + \begin{pmatrix} \sigma_\varepsilon \varepsilon_{int} \\ \sigma_\psi \psi_{int} \end{pmatrix}, \tag{30}$$

where $\varepsilon_{int}$ and $\psi_{int}$ follow idiosyncratic, unit-variance Gaussian white noise processes that are independent of the $u$ process and the $\nu_n$ process as well as independent of each other; and (iv) the constraint on information flow

$$\forall t = 1, 2, \ldots : \underbrace{H(p^{\diamond A}_{int}|s^{t-1}_{in}) - H(p^{\diamond A}_{int}|s^t_{in})}_{\kappa^A} + \underbrace{H(p^{\diamond S}_{int}|s^{t-1}_{in}) - H(p^{\diamond S}_{int}|s^t_{in})}_{\kappa^S} \leq \kappa. \tag{31}$$

Here $H(X|\mathscr{I})$ denotes the conditional entropy of $X$ given the information set $\mathscr{I}$, which is a measure of the conditional uncertainty of $X$ given $\mathscr{I}$. The difference $H(X_t|s^{t-1}_{in}) - H(X_t|s^t_{in})$ is a measure of the reduction in uncertainty about $X_t$ that is due to the new signal received in period $t$. Sims (2003, Section 5) suggested using this measure of uncertainty reduction to quantify the amount of information received by the decision-maker in period $t$. The information flow constraint (31) states that, in each period $t \geq 1$, the information flow is limited. The information flow concerning aggregate conditions, denoted $\kappa^A$, plus the information flow concerning sector-specific conditions, denoted $\kappa^S$, cannot exceed the value $\kappa$.

The optimal allocation of attention (i.e. a pair $\kappa^A$ and $\kappa^S$ with $\kappa^A + \kappa^S \leq \kappa$) is derived under two different assumptions about the value of the overall attention devoted to the price setting decision (i.e. $\kappa$). In the benchmark specification of the model, it is assumed that the decision-maker can choose the overall attention devoted to the price setting decision facing the cost function $c(\kappa) = \phi\kappa$, where $\phi > 0$ is the real marginal cost of devoting attention to the price setting decision. This cost can be interpreted as an opportunity cost (devoting more attention to the price setting decision means devoting less attention to some other decision) or a monetary cost (e.g. a wage payment). Formally, the term $[\beta/(1-\beta)]c(\kappa)$ is added to the objective (25) and the variable $\kappa$ is added to the vector of choice variables. In an alternative specification of the model, it is assumed that $\kappa$ is fixed. Similarities and differences of these two specifications are discussed below.

It is worth pointing out that the assumption that the noise terms in Eq. (30) are independent captures the idea that paying attention to aggregate conditions and paying attention to sector-specific conditions are separate activities. This assumption is discussed in detail and relaxed in Section VIIB of Maćkowiak and Wiederholt (2009a).

Finally, to abstract from transitional dynamics in conditional variances, it is assumed that at the end of period zero (i.e. after the decision-maker has chosen the precision of the signals) the decision-maker receives information such that the conditional variances of $p^{\diamond A}_{in1}$ and $p^{\diamond S}_{in1}$ given information in period zero equal the steady-state values of the conditional variances of $p^{\diamond A}_{int}$ and $p^{\diamond S}_{int}$ given information in period $t-1$. This simplifies computing the solution to problem (25)–(31).

To begin consider the price setting behavior for a given allocation of attention (i.e. for a given pair $\kappa^A$ and $\kappa^S$). One can show that the price setting behavior for a given allocation of attention satisfies the following equation[24]:

$$p^{\diamond}_{int} - p_{int} = \sum_{l=0}^{\infty}[(2^{-2\kappa^A})^{l+1}\sigma_A u_{t-l} - (2^{-2\kappa^A})^l(2^{-\kappa^A})\sigma_A \varepsilon_{int-l}] + \sum_{l=0}^{\infty}[(2^{-2\kappa^S})^{l+1}\sigma_S \nu_{nt-l} - (2^{-2\kappa^S})^l(2^{-\kappa^S})\sigma_S \psi_{int-l}], \tag{32}$$

where $p^{\diamond}_{int} - p_{int}$ is the difference between the profit-maximizing price and the actual price. The speed at which the gap $p^{\diamond}_{int} - p_{int}$ closes after an innovation in the aggregate component, $u_t$, depends on the attention allocated to aggregate conditions, $\kappa^A$; and the speed at which the gap closes after an innovation in the sector-specific component, $\nu_{nt}$, depends on the attention allocated to sector-specific conditions, $\kappa^S$. Hence, if the decision-maker pays more attention to sector-specific conditions than to aggregate conditions ($\kappa^S > \kappa^A$), the price set by firm $i$ in sector $n$ responds faster to sector-specific shocks than to aggregate shocks.

The remaining question is the following. How much attention will the decision-maker devote to aggregate conditions and how much attention will the decision-maker devote to sector-specific conditions? Substituting the price setting behavior for a given allocation of attention into expression (25) yields the expected discounted sum of profit losses for a given allocation of attention[25]:

$$\frac{\beta}{1-\beta}\frac{\bar{C}(\theta-1)\left(1+\frac{1-\alpha}{\alpha}\theta\right)}{2}\left(\frac{\sigma_A^2}{2^{2\kappa^A}-1}+\frac{\sigma_S^2}{2^{2\kappa^S}-1}\right). \tag{33}$$

It is now straightforward to derive the optimal allocation of attention.

[24] See Appendix C available on Science Direct.
[25] See again Appendix C available on Science Direct.

When the decision-maker in a firm chooses the overall attention devoted to the price setting decision facing the cost function $c(\kappa) = \phi\kappa$, the decision-maker equates the marginal value of attending to aggregate conditions to the marginal cost of attention. Furthermore, the decision-maker equates the marginal value of attending to sector-specific conditions to the marginal cost of attention. Formally,

$$\frac{\bar{C}(\theta-1)\left(1+\frac{1-\alpha}{\alpha}\theta\right)}{2}\frac{\sigma_A^2 2^{2\kappa^A}}{(2^{2\kappa^A}-1)^2}2\ln(2) = \phi \tag{34}$$

and

$$\frac{\bar{C}(\theta-1)\left(1+\frac{1-\alpha}{\alpha}\theta\right)}{2}\frac{\sigma_S^2 2^{2\kappa^S}}{(2^{2\kappa^S}-1)^2}2\ln(2) = \phi. \tag{35}$$

Rearranging these two equations yields

$$2^{\kappa^A} - \frac{1}{2^{\kappa^A}} = \sigma_A\sqrt{\frac{\bar{C}(\theta-1)\left(1+\frac{1-\alpha}{\alpha}\theta\right)}{\phi}\ln(2)} \tag{36}$$

and

$$2^{\kappa^S} - \frac{1}{2^{\kappa^S}} = \sigma_S\sqrt{\frac{\bar{C}(\theta-1)\left(1+\frac{1-\alpha}{\alpha}\theta\right)}{\phi}\ln(2)}. \tag{37}$$

The model predicts that price setters devote more attention to aggregate conditions when aggregate conditions are more volatile. Similarly, the model predicts that price setters devote more attention to sector-specific conditions when sector-specific conditions are more volatile. Dividing Eq. (37) by Eq. (36) yields

$$\frac{2^{\kappa^S}-2^{-\kappa^S}}{2^{\kappa^A}-2^{-\kappa^A}} = \frac{\sigma_S}{\sigma_A}. \tag{38}$$

One arrives at the following prediction of the model. When the sector-specific component of the profit-maximizing price is more volatile than the aggregate component of the profit-maximizing price ($\sigma_S > \sigma_A$), price setters devote more attention to sector-specific conditions than to aggregate conditions ($\kappa^S > \kappa^A$), implying that prices respond faster to sector-specific shocks than to aggregate shocks.

In the derivation above it was assumed that decision-makers in firms can choose the overall attention devoted to the price setting decision facing the cost function $c(\kappa) = \phi\kappa$. When one assumes instead that $\kappa$ is fixed, the optimal allocation of attention is given by (i) the optimality condition that the marginal value of attending to aggregate conditions has to equal the marginal value of attending to sector-specific conditions and (ii) the constraint $\kappa^A + \kappa^S = \kappa$. The optimality condition is exactly Eq. (38). Hence, the predictions concerning the relative speed of response of prices to shocks are the same as before. The difference is that now the attention devoted to aggregate conditions depends both positively on $\sigma_A$ and negatively on $\sigma_S$. This can be seen by substituting the constraint $\kappa^A + \kappa^S = \kappa$ into the optimality condition (38). By contrast, with a constant marginal cost of attention, the attention devoted to aggregate conditions does not depend on $\sigma_S$. See Eq. (36).

Finally, integrating Eq. (32) over all $i$ and using Eqs. (9) and (26)–(28) yields an equation for the sectoral inflation rate that has the form of Eq. (1), which is the equation that we estimate.[26]

The remainder of this subsection summarizes several predictions of this model and points out additional predictions of the model. First, if in a sector the sector-specific component of the profit-maximizing price is more volatile than the aggregate component of the profit-maximizing price, then the sectoral price index responds faster to sector-specific shocks than to aggregate shocks.

Second, a sectoral price index responds faster to aggregate shocks the larger the standard deviation of the profit-maximizing price due to aggregate shocks; and a sectoral price index responds faster to sector-specific shocks the larger the standard deviation of the profit-maximizing price due to sector-specific shocks. Furthermore, when price setters in firms face an exogenous information-processing limit or when price setters in firms can decide to process more information subject to a strictly convex cost function, the speed of response of a sectoral price index to aggregate shocks depends both positively on the standard deviation of the profit-maximizing price due to aggregate shocks and negatively on the standard deviation of the profit-maximizing price due to sector-specific shocks.

[26] In the Calvo model, the sectoral price level is given by Eqs. (13) and (14). In the sticky-information model, the sectoral price level is given by Eq. (22). Hence, in these two models, the equation for the sectoral inflation rate also has the form of Eq. (1) when the profit-maximizing price (12) follows a Gaussian process with a time-invariant moving-average representation.

Third, if on average across sectors the sector-specific component of the profit-maximizing price is more volatile than the aggregate component of the profit-maximizing price, then the cross-sectional variation in the speed of response of sectoral price indexes to sector-specific shocks is smaller than the cross-sectional variation in the speed of response of sectoral price indexes to aggregate shocks. Intuitively, when price setters already pay close attention to sector-specific shocks, increasing the standard deviation of sector-specific shocks has little effect on the speed of response of prices to sector-specific shocks. Formally, Eq. (32) and the equations characterizing the optimal allocation of attention imply that the speed of response of prices to a given type of shock is concave in the standard deviation of the shock.

Fourth, if on average across sectors the sector-specific component of the profit-maximizing price is more volatile than the aggregate component of the profit-maximizing price, then the coefficient in the regression reported in the first row of Table 2 should be larger than the coefficient in the regression reported in the third row of Table 2. The reason is again that, according to this model, the speed of response of prices to a given type of shock is concave in the standard deviation of the shock.

It is remarkable that all these predictions are supported by the data.

Boivin et al. (2009) found a positive coefficient in the regression of the speed of response of sectoral price indexes to aggregate shocks on the standard deviation of sectoral inflation due to sector-specific shocks. It is worth pointing out that this finding is consistent with the rational-inattention model described above. The reasons are as follows. First, the model predicts a positive coefficient in the regression of the speed of response to aggregate shocks on the standard deviation of sectoral inflation due to aggregate shocks. Second, the model predicts a negative coefficient in the regression of the speed of response to aggregate shocks on the standard deviation of sectoral inflation due to sector-specific shocks *after controlling* for the standard deviation of sectoral inflation due to aggregate shocks. Third, in the data there is a strong positive relationship between the standard deviation of sectoral inflation due to aggregate shocks and the standard deviation of sectoral inflation due to sector-specific shocks. Therefore, a positive coefficient in the regression of the speed of response to aggregate shocks on the standard deviation of sectoral inflation due to sector-specific shocks is to be expected when one fails to control for the standard deviation of sectoral inflation due to aggregate shocks.[27]

### *7.5. Menu cost model*

Since sectoral price indexes respond quickly to sector-specific shocks, which are large on average, and sectoral price indexes respond slowly to aggregate shocks, which are small on average, one could imagine that a menu cost model can match the empirical findings presented in Sections 4 and 5. However, in a menu cost model, when a firm changes its price, the firm responds to both aggregate and sector-specific conditions independent of what triggered the price change. Thus, when firms respond quickly to sector-specific shocks and sector-specific shocks hit frequently, then firms also respond quickly to aggregate shocks. Hence, it seems that a menu cost model that can match the empirical findings presented in Sections 4 and 5 would have to be a menu cost model with infrequent sector-specific shocks.[28] However, note that Section 6.1 provides evidence suggesting that (i) after dropping a few outlier sectors, sector-specific shocks are approximately Gaussian and (ii) the empirical findings presented in Sections 4 and 5 are not driven by the few sectors experiencing non-Gaussian sector-specific shocks.

## 8. Conclusions

In order to evaluate models of price setting, this paper estimates a dynamic factor model using sectoral price data. Three kinds of results emerge. First, the median impulse responses of sectoral consumer price indexes have the following shapes. One hundred percent of the long-run response of a sectoral price index to a sector-specific shock occurs in the month of the shock. By contrast, only 15 percent of the long-run response of a sectoral price index to an aggregate shock occurs in the month of the shock. Second, there is little cross-sectional variation in the speed of response to sector-specific shocks, while there is considerable cross-sectional variation in the speed of response to aggregate shocks. Third, the results from several regressions are reported.

The rational-inattention model developed in Maćkowiak and Wiederholt (2009a) can match most of these empirical findings. The key features of this model are (i) a quick response to sector-specific conditions does not imply a quick response to aggregate conditions and (ii) the speed of response to a given type of shock is positively related to the volatility of the shock. The assumption that attending to aggregate conditions and attending to sector-specific conditions are separate activities is a sufficient condition, but no necessary condition, for the model to have these properties. See Section VIIB in Maćkowiak and Wiederholt (2009a).

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[27] The model also offers two explanations for the positive relationship in the data between the standard deviation of sectoral inflation due to aggregate shocks and the standard deviation of sectoral inflation due to sector-specific shocks. First, there may simply be a positive relationship between the volatility of the profit-maximizing price due to aggregate shocks and the volatility of the profit-maximizing price due to sector-specific shocks. Second, the parameters in objective (25) may differ across sectors. In sectors where pricing mistakes are more costly, firms pay more attention to both aggregate and sector-specific conditions, implying that prices in those sectors respond faster to both aggregate and sector-specific shocks. This raises both the standard deviation of sectoral inflation due to aggregate shocks and the standard deviation of sectoral inflation due to sector-specific shocks.

[28] For a menu cost model with a similar assumption, see Gertler and Leahy (2008).

The standard Calvo model and the standard sticky-information model have difficulties matching these empirical findings. We think that the way in which these models fail gives us a new perspective on these models and suggests ways to modify these models. In the future, it would be interesting to study more formally whether a menu cost model can match these findings. We conjecture that a menu cost model will have difficulties matching jointly the empirical findings reported above and the empirical distribution of sector-specific shocks reported in Section 6.1.

We hope that the empirical findings reported in this paper guide the development of models of pricing and/or information in the future.

## Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version at 10.1016/j.jmoneco.2009.06.012.

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