BANK OF ENGLAND

Working Paper No. 364

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March 2009

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Abstract

This paper uses a factor-augmented vector autoregression technique to examine the role that macroeconomic and sector-specific factors play in UK price fluctuations at the aggregate and disaggregated levels. Macroeconomic factors are less important for disaggregated prices than aggregate ones. There also appears to be significant aggregation bias — the persistence of aggregate inflation series is much higher than the underlying persistence across the range of disaggregated price series. Our results suggest that monetary policy affects relative prices in the short to medium term, and that the degree of competition within industries plays a role in determining pricing behaviour.

Key words: Inflation persistence, disaggregation, principal components.

JEL classification: C3, D4, E31, E52.

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The views expressed in this paper are those of the authors, and not necessarily those of the Bank of England or the Monetary Policy Committee or Daiwa Securities SMBC. We are grateful to Alex Bowen, Stephen Millard, Miles Parker, Simon Price, Garry Young and an anonymous referee for useful comments. All mistakes remain our own. This paper was finalised on 25 November 2008.

The Bank of England's working paper series is externally refereed.

Information on the Bank's working paper series can be found at
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ISSN 1749-9135 (on-line)

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Summary

How do prices respond to changes in interest rates? Most previous work has tried to answer this question by looking at aggregate price measures, such as the consumer prices index (CPI) or the National Accounts consumption deflator. This paper takes a different approach. Following recent work on US data, we examine the behaviour of both aggregate and disaggregated prices in the United Kingdom using a large volume of data covering prices, volumes, money and asset prices.

In this paper, we summarise these data by using 'principal components', or 'factors'. Factor analysis uses linear transformations of data series to identify common components that underlie those series. The 'factors' are calculated by creating combinations of the underlying data series to make new series that in turn capture the largest possible amount of variation in the data set as a whole, while remaining statistically independent of each other. We then use these factors to estimate a simple model (known as a vector autoregression, or VAR), which in this case relates these factors to their previous values and the interest rate. The resulting model is known as a 'factor-augmented vector autoregression', or FAVAR for short.

The advantages of a FAVAR are that it encompasses a large number of data series but, at the same time, is relatively simple to estimate. By estimating a FAVAR on disaggregated data, we are able to examine how individual disaggregated prices respond to monetary policy and other macroeconomic shocks. The model also tells us how important these macroeconomic factors are, compared to sector-specific factors that affect the individual disaggregated series.

Our benchmark results match those of previous studies and suggest that aggregate demand falls before aggregate inflation when interest rates rise. However, our disaggregated results offer a number of insights that are not captured by aggregate models.

- First, while macroeconomic factors are very important for aggregate data such as CPI inflation, they are much less important for disaggregated inflation measures. Sector-specific factors are at least as important for disaggregated prices.
- Second, we find evidence of significant aggregation bias – aggregate inflation is far more closely related to its previous values than disaggregated inflation measures. This suggests that aggregate inflation measures do not offer a good guide to the behaviour of underlying prices. In other words, trying to infer the statistical properties of individual prices from those of aggregate price indices is likely to be misleading.
- Third, different disaggregated prices respond differently to changes in interest rates, suggesting that monetary policy can affect relative prices in the economy.
- Fourth, there is some evidence that competition within industries plays a role in determining how companies set prices – in particular, companies in less competitive industries may be more able to pass on changes in prices to customers.

1 Introduction

UK monetary policy is concerned with keeping inflation on target at 2% a year. So it is important for policymakers to consider how prices behave: without a good understanding of pricing behaviour, not least how prices respond to monetary policy, policymakers may struggle to achieve price stability.

One common feature of many economic models is some form of 'price stickiness'. Numerous theoretical mechanisms have been proposed to underpin this assumption, including costs of adjusting prices (Rotemberg (1982), Mankiw (1985)), staggered contracts (Taylor (1980)), threshold pricing (Sheshinski and Weiss (1977)), and fixed probabilities of being able to change prices (Calvo (1983)).[(1)] One popular pricing model that results from the last approach is the so-called New Keynesian Phillips Curve (NKPC). Previous estimates of this model imply that on average, firms change their prices every five to six quarters (Gali and Gertler (1999)), although some studies suggest once every two years (Smets and Wouters (2003)).

The estimates reported above are based on aggregate data and exceed the timings reported in direct surveys of companies' price-setting behaviour. For example, Blinder *et al* (1998) and Druant *et al* (2005) both find that the median price changes once a year in the United States and the euro area, respectively. Recent studies, also based on disaggregated data, suggest that individual prices may be even more flexible than this. In particular, Amirault *et al* (2005) and Bils and Klenow (2004) found that prices change on average every three to four months.[(2)] And evidence from 300 of the Bank of England's Agency contacts suggests that half of companies change prices at least five times a year (Bank of England (2006)).

A useful first step in trying to understand the discrepancies between macro and micro-data based estimates would be to analyse the behaviour of aggregate and disaggregated prices in a single, consistent framework. Boivin, Giannoni and Mihov (2007, hereafter BGM) have recently demonstrated how this can be done using US data. Their innovative approach uses the factor-augmented vector autoregression (FAVAR) methodology developed by Bernanke, Boivin and Eliasz (2005, hereafter BBE) and allows large amounts of data to be incorporated into the estimates (in contrast to most standard economic models). Apart from providing evidence on whether aggregate price measures accurately represent individual (sectoral) pricing behaviour, the FAVAR methodology makes it possible to differentiate between price changes that reflect common, or macroeconomic, factors, and sector-specific concerns. Accordingly, it might also be helpful in trying to account for the considerable heterogeneity among companies and sectors found in different direct studies of price-setting.

In this paper, we follow BGM's approach for the United Kingdom, using disaggregated consumer expenditure data. However, we also identify a model using sign restrictions as well as the Cholesky method, following recent work on VARs. In common with BGM's US results, we find that

(1) By themselves, these sticky price mechanisms do not typically capture the persistence in aggregate inflation (Lendvai (2006)), and *ad hoc* adjustments are typically added to improve the fit of the model.
(2) Allowing for sales and special promotions, Nakamura and Steinsson (2007) find the median duration of retail prices is between eight and eleven months.

disaggregated price series exhibit less persistence than aggregate measures would imply, and that sector-specific factors are important for determining fluctuations in disaggregated prices. Our results suggest that monetary policy affects relative prices in the short to medium term, and that the degree of competition in sectors is significantly correlated with the behaviour of prices.

The rest of this paper is structured as follows. Section 2 sets out the methodological approach used, and describes the data set. Section 3 presents results from this approach for aggregate variables. Section 4 then presents results using the disaggregated consumer expenditure data, and Section 5 looks at how these results relate to other sectoral information. Section 6 concludes.

2 Methodology

The FAVAR approach pioneered by BBE assumes that there are a number of common factors that affect all variables in the economy: the economy itself is measured as a large data set X_t that contains many different series. The common factors or components, C_t, may reflect underlying economic conditions such as 'activity' or 'pricing pressure'. They are estimated as the first K principal components of X_t. These components, or factors, then form the variables that are included in an estimated VAR model. From the resulting VAR estimates, responses for the original data series can be derived from the eigenvectors associated with the (common) principal components.(3)

One important issue with all VAR models is how to identify economic shocks. BGM identify monetary policy by explicitly including the policy rate (ie the Federal funds rate), R_t, as one of the common factors (see also Boivin, Giannoni and Mihov (2007) for more details). They then order the Federal funds rate last, and treat its innovations as monetary policy 'shocks', ie effectively, they use the Cholesky identification method. This method, however, has been criticised by a number of authors, including Canova and de Nicolo (2002) and Uhlig (2005) on the grounds that it may be more stringent than is borne out by the data. As a less restrictive alternative, those authors propose an identification system based on sign restrictions. In essence, sign restrictions force the initial response of individual variables to be either positive or negative, but impose no assumptions on the adjustment path that follows (see also Uhlig (2005) for more details on this identification method).

In order to use sign restriction based identification, we must place some interpretation on the principal components in the VAR.(4) To allow us to do so, we partitioned the data set of macro variables into different categories, grouping activity, price, money and asset price variables separately. By taking principal components from the resulting partitions of the data set, we could retrieve common components that were plausibly interpretable as 'activity' or 'price' factors. In other words, we interpret the first principal component of the collection of activity factors as an 'activity' factor, etc. This then allows us to use sign restrictions to identify the VAR, and compare it with BGM's original Cholesky identification method.

Technically, our model can be represented by the following two equations

(3) More information on the FAVAR approach is available in BBE. The authors also describe an alternative implementation method, which is a single-step Bayesian likelihood approach. For simplicity, we follow the two-step principal components approach. Stock and Watson (2005) explore how many factors should be included in the VAR.
(4) For example, the assumption that activity initially falls in response to a negative demand shock requires us to identify one of the common components as an 'activity' variable.

$$\begin{pmatrix} Y_{1,t} \\ Y_{2,t} \\ . \\ . \\ R_t \end{pmatrix} = \begin{pmatrix} B_{11} & . & . & . & B_{1N} \\ B_{12} & . & & & \\ . & & . & & \\ . & & & . & B_{NN} \\ 0 & 0 & . & . & 1 \end{pmatrix} \begin{pmatrix} F_{1,t} \\ . \\ . \\ F_{N,t} \\ R_t \end{pmatrix} + \begin{pmatrix} v_{1,t} \\ . \\ . \\ v_{N,t}. \\ 0 \end{pmatrix}$$

$$Z_t = c + \sum_{j=1}^{L} \rho_j Z_{t-j} + \varepsilon_t$$

where $Z_t = \{F_{1,t},...F_{N,t}, R_t\}$. Here, $Y_{1,t},...Y_{N,t}$ represent portions of our data set corresponding to different macroeconomic variables. For example, $Y_{1,t}$ gathers together all our data on real activity, $Y_{2,t}$ contains inflation, etc. $F_{1,t},...F_{N,t}$ denote the unobserved factors that are extracted from this data set, while $B_{i,i}$ represent (blocks) of factor loadings. R_t denotes the policy rate, which we treat as an observed factor.

As mentioned above, we extract the factors in two ways. In our benchmark model, we assume that the factor loading matrix is full. That is, we extract *N* factors from the entire data set without considering the different blocks of data separately. Our alternative model imposes the restriction that the off-diagonal elements of the factor loading matrix equal zero. In other words, the factors are extracted from blocks of the data corresponding to real activity, inflation, money and asset prices.

We use the principal component estimator employed by BBE to extract the factors. Note that the estimator incorporates the normalisation that $B'B = I$. This is required because the principal components are subject to rotational indeterminacy and are econometrically unidentified.

The dynamics of the factors and the policy rate are described by a VAR shown in the second equation above. We estimate the model in two steps, using the principal component estimates of the factors obtained in the first step. As the number of endogenous variables in our model is quite high, we use a Bayesian estimator. This allows us to incorporate inexact prior restrictions described in Sims and Zha (1998) into the analysis: in particular, our inexact prior restriction was that the variables followed a first-order autoregressive process. We approximate the posterior distribution using Gibbs sampling. Details on the conditional posterior distributions are available in Uhlig (2005).

2.1 Data

Our data set comprised around 60 macroeconomic UK data series, running from 1977 Q1 to 2006 Q3. It included activity measures such as GDP, consumption and industrial production, various price measures including RPI, CPI and the GDP deflator, as well as money and asset price data. Where appropriate, variables were log-differenced to induce stationarity. In addition to these macro variables, we included a large number of disaggregated deflator and volume series for consumers' expenditure. The Office for National Statistics (ONS) publishes over 140 subcategories of consumer expenditure data in value, volume and deflator terms, going back to the 1960s.[5] This gives us a ready-made collection of consistent disaggregated price (and volume) data over a long time period.

3 Results: aggregate variables

Before examining the response of disaggregated price series, we estimated 'baseline' models for the UK macroeconomy. The first of these was a standard five-variable VAR, with CPI inflation, GDP growth, M4 growth, the UK sterling exchange rate index (ERI) and Bank Rate.[6] This basic VAR model offers a benchmark to compare our later FAVAR models to. Chart 1 shows impulse responses of the five variables in this VAR to a monetary policy contraction.[7] As is the case with several other VAR models, our responses suggest that GDP and M4 growth fall after the policy contraction, but also that CPI inflation *rises* after the monetary policy shock. This is the well documented 'price puzzle' pointed out by Sims (1992).

The second model we estimated was a FAVAR. Here, we followed BGM's identification approach and explicitly identified monetary policy shocks. The model contained eight factors (plus the monetary policy variable, R_t).[8] Chart 2 shows the resulting impulse responses for CPI inflation, GDP growth and other variables in this model to a 100 basis point (bp) rise in Bank Rate.

Some features of the responses are worth highlighting.[9]

- First, median CPI rises following a monetary policy contraction. While not statistically significant, this is in contrast to BGM, who do not find such a price puzzle in their aggregate responses. Since recent work suggests that this 'puzzle' may actually reflect a misspecification of the underlying VAR model (Giordani (2004), Castelnuovo and Surico (2006)) this could indicate that our set-up is not free of similar problems.
- Second, the median response suggests that CPI inflation starts to fall (relative to the counterfactual of no policy innovation) almost two years after the initial policy shock. This 'delayed response' of inflation is not uncommon in other models. But it is somewhat longer than other large models of the UK economy: for example, using a large structural macro model Harrison *et al* (2005) find that the maximum impact of interest rates on CPI inflation occurs between one and two years after the interest rate shock.[10]

Taken together, these features suggest we may want to verify the robustness of our findings and consider alternative versions of the model. In the light of external concerns about BBE's

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(5) See ONS (2007).
(6) Unless otherwise stated, all the results in this paper are based on models with two lags: (quarterly) growth rates are calculated as log differences.
(7) The model is identified using a standard Cholesky ordering. This VAR (and the other FAVAR models) was estimated using Bayesian techniques, which are used to derive the standard errors. In all instances, little weight was imposed on the simple autoregressive priors. One standard error bands are shown in red throughout this paper.
(8) This is broadly in line with Stock and Watson (2005) who find that seven factors are appropriate for modelling the US economy. Our results support this view: adding further factors had little impact on our results.
(9) Chart 3 shows the underlying factors used in this FAVAR.
(10) In other words, the trough in the impulse response should occur at around two years, rather than the response finally becoming negative at that point. The estimated impulse response troughs almost four years after the policy change, which is also significantly higher than stated Bank priors of around a year.

identification scheme, expressed for example in Stock and Watson (2005), we estimated another FAVAR where shocks were identified using sign restrictions, rather than Cholesky ordering.

As mentioned in the methodology section, in order to identify the model using sign restrictions, we need to place some economic interpretation on the factors. As such, it is appropriate to present them for scrutiny. Chart 4 shows the four key principal components from the partitioned macro data set,[11] where we grouped variables into four categories: activity; prices; money; and asset prices. While volatile, the 'activity' factor closely corresponds to cyclical estimates for the UK economy (Ellis and Turnbull (2007)), the 'inflation' factor resembles key price variables such as CPI and RPI while the 'asset price' factor is reminiscent of interest rate data.[12]

In identifying the model, we imposed the sign restrictions on the model based on three types of shocks: demand, supply, and monetary policy. The sign restrictions force the initial responses of the FAVAR variables to be either positive or negative. Our restrictions were chosen to match standard theoretical prior beliefs from DSGE models – for example, in response to a positive supply shock, we imposed that output would rise in the first instance, and inflation fall. The full set of identifying restrictions we used is presented in Table A.[13]

Chart 5 shows the impulse responses of macro variables to a 100bp rise in this alternative FAVAR model. Now, the largest impact on CPI inflation occurs around two years after the shock. Similarly, the biggest impact on GDP is after a year or so, consistent with Bank of England (2004).[14] While this model appears more consistent with previous Bank work, it is important not to overplay the differences between the two sets of results. Both models find that output falls, and then inflation, in response to a monetary policy shock. Both models find that the impact of monetary policy on aggregate inflation is temporary, with inflation returning to base over time. These consistencies lend support to both identification methods.

One advantage the sign-restriction model offers is the ability to analyse the impact of other shocks that hit the economy, not just changes in monetary policy. Chart 6 shows responses of macro variables to a supply shock – an unexpected decrease in productive capacity. As we might expect, inflation rises in response, while activity falls in the short term. Chart 7 shows responses to a demand shock – an unexpected rise in demand. Once again, our sign-restriction model fits standard theoretical priors well.

Our 30-year data period covers a number of changes in the UK economy – most noticeably, in a policy context, the shift to inflation targeting in 1993. Accordingly, before examining disaggregated data, as a final robustness check, we tested for the presence of a structural break in our model. To examine whether the policy responses were affected, we estimated a version of the Cholesky model with a dummy variable from 1993 onwards. The results are shown in Chart 8.

(11) That is, those principal components that we placed the sign restrictions on to identify the VAR.
(12) It is worth noting that we included a total of ten factors in the sign-restriction FAVAR. This included four inflation and four activity factors. Due to the partitioning, disaggregated price and quantity results (presented later) will be based only on those pricing and activity factors included in the model. As such, we wanted to include more than one factor, to try to capture a greater degree of variance in the disaggregated series.
(13) By construction there is no 'price puzzle' here in our 'pricing' factor, as it is constrained to fall following a contractionary monetary policy shock.
(14) In the next section, we explore the differences between the Cholesky and sign-restriction models in more detail.

Although the standard errors are larger for estimates from 1993 onwards, as we would expect given the smaller amount of data, the median impulse responses are very similar, giving us increased confidence in the robustness of our findings.

So, in summary, we have two FAVAR models with which to examine the behaviour of disaggregated prices. In the following sections, we compare the results from both.

4 Results: disaggregated prices

Having established our baseline FAVAR models, we then examined the dynamics of the disaggregated consumer expenditure data. In total, we included over 140 different expenditure categories.[15] Chart 9 plots the response of the aggregate consumption deflator (red) and the individual disaggregated deflators (blues) to a contractionary monetary policy shock in our Cholesky FAVAR. (Charts 10-11 plot the corresponding responses for the individual price levels.) Chart 12 plots the inflation and price-level responses in our sign-restriction FAVAR (individual disaggregated responses are shown in Charts 13-14).

Overall, the two sets of model results are broadly consistent – for example they both exhibit a range of responses among the disaggregated prices, in terms of magnitude and speed. Both models suggest that some disaggregated prices respond swiftly to the contractionary monetary policy shock – and many inflation rates move quickly as well. At the same time, both models imply that some disaggregated prices take a little longer to respond, in line with BGM's finding that some disaggregated US prices took six months to respond.

But there are also some differences between the two sets of model results – in particular the range of the disaggregated impulse responses in each model, where responses in the sign-restriction model are more marked than those in the Cholesky one.[16] The model identification method appears to be very important for gauging the spread of disaggregated price responses. In part, this could reflect the fact that responses in the Cholesky model are based on all of the eight macro factors, whereas responses in the sign-restriction version are based on the four factors from the relevant data partitions.

In order to try and find the factors responsible for differences between both sets of results, we experimented with a variety of changes. Charts 9 and 12 are both based on FAVARs estimated over the whole data sample, and each model has two lags, so the underlying data cannot account for the differences. When we expanded the sign-restriction model, so that there were eight factors in the output and price partitions, the different results remained: so this does not appear to be the driving factor. Finally, when we attempted to estimate a model by placing sign restrictions on the Cholesky factors (Chart 3), we retrieved impulse responses with a wider range than was present

[15] Some of these categories were subindices of the underlying series, but most were the highest level of disaggregation that was readily available.
[16] Another difference relates to price puzzles: there is some evidence of price puzzles in the disaggregated data using the Cholesky approach, in relative contrast to evidence from the sign-restriction FAVAR. But this is unsurprising, given our identification methods and the associated responses of aggregate inflation. The lack of a generalised price puzzle is consistent with BGM's results.

when those factors were modelled using the Cholesky identification method. This suggests that the different identification methods do account for the difference in the range of the impulse responses. We take some comfort from the fact that Peersman (2005) also compares a sign-restriction model to a model with traditional restrictions, and finds similar results, in that the maximum impact of a monetary policy shock is larger in the sign-restriction model.

The impulse responses also tell us about how different prices respond. In particular, they show that a monetary policy shock has an impact on the relative prices of different goods and services – some prices are little affected (the cumulative response is close to zero) while others are more markedly affected (the cumulative response is large and persistent). At first sight this may seem counterintuitive. But it is worth remembering that our shock is not a 'pure' monetary shock in the sense of an exogenous decrease in the money supply. An increase in interest rates can reduce demand via different channels. One channel is via the reallocation of income from interest-paying debtors to interest-receiving creditors. If debtors and creditors have different preferences for spending on ranges of goods and services,[17] then this reallocation of income could have a persistent impact on relative prices.[18] Despite these changes in relative prices, the long-run impact of policy on aggregate consumption is broadly neutral, as we might expect.

One interesting question is whether the relative price changes are significant or not. To investigate this, we examined whether the response of individual price changes was significantly different from average inflation. Using a benchmark 10% significance level, we would expect 10% of sectoral prices to be different at any given time. Charts 15 and 16 show the proportion of sectors where individual sectors exhibit significantly different inflation from the average. The results do vary across the two models, but the consistent finding is that although there are some significant relative price effects in the short to medium term, there is no evidence of significant effects in the long run.

Our sign-restriction model also lets us examine the disaggregated responses of prices and volumes to demand and supply shocks. These responses are shown in Charts 17 and 18. As with the monetary policy shock, there is considerable heterogeneity among the disaggregated responses. One interesting feature of both sets of responses is that (aggregate and disaggregate) prices respond by more than volumes to all three shocks (monetary policy, supply and demand).

In addition to these dispersed impulse responses, we can use the FAVAR to examine the roles that macro factors play – measured here using our principal components – as well as sector-specific factors, measured using residuals. In other words, the FAVAR allows us to analyse the extent to which (sectoral) inflation rates reflect either macroeconomic or sectoral developments.

Tables B and C report summary statistics on the volatility and persistence of both aggregate and disaggregated quarterly inflation series for our two FAVAR models.[19] In line with BGM's results, we find that the majority of the volatility in aggregate inflation rates is due to fluctuations in the

[17] This could follow if consumption preferences change with age, as younger people tend to have higher debts than older people: see Waldron and Young (2006).
[18] An alternative channel is via changes in interest rates affecting the user cost of durable goods: see Power (2004).
[19] These tables correspond to Table 1 in BGM.

common components (the exception being wages, where sector-specific factors matter more). However, for disaggregated inflation measures this is not true – for many disaggregated series, volatility is more commonly due to sector-specific factors, rather than the common macroeconomic factors. Unsurprisingly, there is considerable heterogeneity among the disaggregated series. Encouragingly, the results are very similar across both models, suggesting they are robust to the choice of identification scheme.

There is also a marked difference in the persistence of the series. We assessed this by estimating AR(1) models for each inflation series and their components, namely the common factors and the sector-specific components. In common with BGM, we found that the aggregate inflation measure exhibited a high degree of persistence, but that the disaggregated series exhibited far less persistence.(20)

This difference between estimates of persistence at the aggregate and disaggregate level is marked – the persistence of the aggregate consumption deflator is not the average persistence of the underlying component series. This might partly reflect individual weightings in the consumption basket, which we have not explicitly taken account of here. But aggregation bias also plays a crucial role. As Imbs *et al* (2005) demonstrate in a PPP context, aggregate measures of persistence will be biased when there is heterogeneity in persistence among the disaggregated components. In particular, aggregate estimates of persistence will be biased upwards, ie will be higher than the average persistence of the underlying disaggregated series.(21) Mojon *et al* (2007) find very similar results to ours for euro-area prices: fast adjustment in disaggregated series sits alongside slow adjustment at the aggregate level. They conclude that aggregation explains a fair amount of aggregate inflation persistence.(22)

The same thing is happening here – the persistence of aggregate inflation is biased upwards, rather than simply being an average of the underlying series' individual persistence. Importantly, this means that using an aggregate inflation measure to gauge the typical behaviour of prices or price-setting at the microeconomic level might be misleading, as disaggregated prices do not behave the same way as aggregate indices. This in turn has implications for micro-founded models that characterise micro-behaviour based on aggregate inflation measures.(23)

Interestingly, there is little evidence that sector-specific factors were important in determining persistence, for either aggregate or disaggregated series. What persistence is present is driven by the common macro components – and the fact that these are less important for disaggregated prices than aggregate ones is consistent with disaggregated prices exhibiting less persistence overall. This suggests that any persistence in prices is driven by persistence in the macroeconomy, such as

(20) For example, the AR(1) for the aggregate consumption deflator was 0.770, but the AR(1) for the median disaggregated series was 0.304.
(21) This is in contrast to some other mechanisms, where sticky prices at the micro level can still be consistent with flexible prices at the macro level (Caplin and Spulber (1987)).
(22) Imbs *et al* (2007) introduce heterogeneity in price-setting behaviour across industries, and find that homogeneous models overestimate the apparent backward-looking behaviour in prices.
(23) Aoki (2001) argues that the optimal price index policymakers should target would place more weight on the prices that are sticky, and less weight on the prices that are more flexible. The fact that the persistence of aggregate inflation measures are biased upwards suggests that, implicitly, targeting an aggregate inflation measure may (partially) account for this.

activity or policy, and that sector-specific shocks are transitory in nature. This is consistent with sector-specific shocks playing little role at the aggregate level.

So, in summary, disaggregated inflation rates are significantly less persistent than aggregate measures, reflecting the role of aggregation bias. Disaggregated price changes are not very sticky. In addition, sector-specific factors are just as important for disaggregated prices as macroeconomic developments. In the next section, we examine whether these sector-specific factors are related to other sectoral characteristics.

5 The role of sectoral characteristics

The behaviour of disaggregated prices depends more on sector-specific factors than on macroeconomic developments. But can we say anything about how those sector-specific factors relate to sectoral characteristics? One simple test is to examine the relationship between the disaggregated impulse responses to a monetary policy shock and the estimated role that sector-specific factors play – as characterised by the volatility and persistence of sector-specific components in Tables B and C.

Table D presents correlations between these data.[24] There is evidence of a positive correlation between the variance of sector-specific factors and the response to monetary policy of sectoral prices. But, as our responses are to a contractionary monetary shock, this implies that companies who face larger sectoral shocks respond less (ie their response is more positive) to policy. This is consistent with both the state dependent pricing literature (see eg Dotsey *et al* (1997)) and the rational inattention literature pioneered by Sims (2003) and further developed by Reis (2006) and Mackowiak and Wiederholt (2007). The latter suggests that in the face of higher idiosyncratic volatility, relatively more attention should be put on idiosyncratic shocks than monetary policy shocks and hence the speed of response of the latter should be small (in line with the correlation we find). On the other hand, the result appears to contrast with the findings of Gertler and Leahy (2006), which suggest that the more companies are affected by idiosyncratic shocks, the more they adjust prices to a monetary policy shock.

We can also compare results from the model to other sectoral information, such as competition measures. In particular, we gathered four pieces of sectoral data, based on Supply-Use tables and other published work: the gross profit share; the ratio of imports to gross output; and two concentration ratios,[25] taken from Mahajan (2006). These data are available on an industry basis, rather than a disaggregated product basis – so we had to match the relevant disaggregated price series to the industry data. In some cases this was straightforward, but occasionally rather heroic assumptions were required. In total, we matched about 50 different disaggregated prices to our industry-level 'competition' measures.

Table E reports correlations between these four industry measures and sector-specific results from our two FAVAR models, namely: accumulated impulse responses to monetary policy shocks;

[24] Chart 19 plots the ten-quarter response against sector-specific variance for the sign-restriction FAVAR.
[25] Output of the largest 5% and largest 15% of businesses as a percentage of total sectoral output.

sector-specific variances; and sector-specific persistence. There is some evidence of significant correlations between impulse responses and sectoral characteristics. However, this evidence is not robust to model identification, reflecting the fact that disaggregated impulse responses in the two models are not always very similar.

However, there is a robust positive correlation between the size of sector specific fluctuations and the concentration ratio. This is consistent with sector-specific shocks having bigger effects in less competitive industries – perhaps because less competition allows companies to pass on changes in price more easily. In contrast, more competitive sectors may be unable to adjust their prices as easily (in a similar way to the correlation with monetary policy responses).

The other correlations that are common to both models relate to the persistence of sector-specific shocks. The profit share is positively correlated with this persistence – implying that sectoral shocks last longer in sectors with larger margins. In contrast, the import share is negatively correlated with sector-specific persistence. One interpretation of this result is that a higher import share implies greater competition (from overseas) – and hence that domestic producers find it harder to make persistent price changes in response to (domestic) sectoral shocks, for example because their foreign competitors do not face the same (sector-specific) shocks. The same logic could apply to the positive margin/persistence correlation, if higher margins are synonymous with less competition, and hence companies find it easier to make price changes persistent in response to sector-specific factors.

This evidence suggests that sector characteristics may be important in determining how different prices behave. Companies in less competitive industries may have more power over changing their prices, and making those changes more persistent. But companies in more competitive industries may find it hard to pass the impact of either sector-specific or macroeconomic shocks on to customers by changing prices.

5.1 Implications for monetary policy

Our results have a number of implications for monetary policy makers. First, and most obviously, BBE’s FAVAR framework allows policymakers to combine the relative simplicity of VARs with the desire to include many different series. Furthermore, these models appear to fit policymaker’s prior beliefs reasonably well, as judged by impulse responses: our results confirm that policy is felt first by activity at the aggregate level, rather than prices.

Our results also suggest that there may be less persistence in individual prices than is suggested by aggregate data. Average persistence among the disaggregated price series is much lower than is evident in the headline series, reflecting aggregation bias. This means that there may be relatively more flexibility in the nominal side of the economy than is evident from aggregate inflation – consistent with our finding that aggregate (and disaggregate) consumption volumes respond less to demand and supply shocks than consumption prices.

Our findings can also be compared with implications from various pricing theories. There are two key results that are particularly relevant: first, that sectoral effects on prices are important and relatively short-lived, while macroeconomic effects are more long-lived; and second, that sectors facing larger idiosyncratic shocks respond less to monetary policy.

These results are inconsistent with the implications from time-dependent sticky-price models. In these models, the source of the shock should not affect the persistence the price response – and hence those time-dependent theories are inconsistent with the different persistence of the sector-specific and macro effects. In the same vein, by themselves time-dependent models do not allow different responses to policy shocks across sectors.

This suggests that, if policymakers want to capture economic relationships accurately, state-dependent rigidities should form the underlying basis of nominal frictions in their models. Of these, some forms of rigidity may be less appropriate than others – for example, menu costs would not allow for the different persistence of idiosyncratic and macro effects, while rational inattention models allow for this possibility. More work is required to examine which theoretical structures match the facts we have uncovered.

6 Conclusions

This paper has examined how aggregate and disaggregated price data respond to both macroeconomic and sector-specific developments in the UK economy. We have employed factor-augmented vector autoregression techniques to characterise the behaviour of the UK economy over the past 30 years, experimenting with two different identification strategies. Our results show that aggregate prices series are more persistent than the majority of the underlying disaggregated series, consistent with evidence of aggregation bias in a number of other studies. In short, aggregate inflation measures do not offer a good guide to underlying pricing behaviour or, in other words, trying to infer the statistical properties of individual prices from those of aggregate price indices is likely to be misleading.

Our results also suggest that what persistence is present in disaggregated prices reflects persistence in macroeconomic developments, rather than sector-specific factors. Disaggregated prices respond reasonably quickly to monetary policy changes, and few exhibit evidence of 'price puzzles', although there is considerable heterogeneity among those prices. One observation from the disaggregated responses is that monetary policy has an impact on relative prices in the short to medium term. Finally, we examine pricing behaviour across sectors, and find that competition within industries is significantly correlated with the behaviour of industry prices.

Appendix: Charts and tables

Chart 1: Impulse responses to a monetary contraction in a five-variable VAR

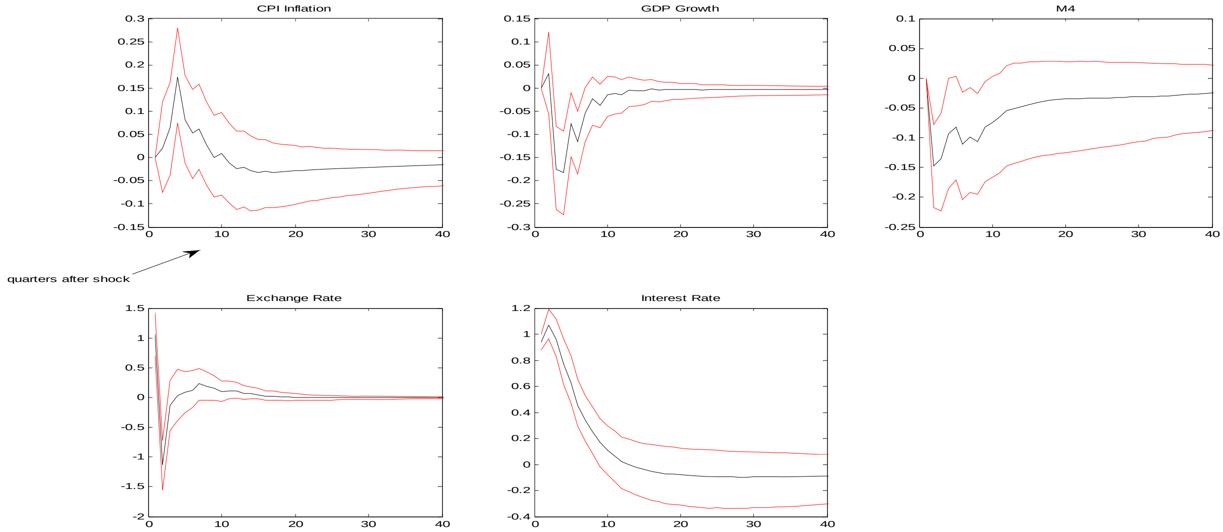

Chart 2: Impulse responses of key variables to a monetary contraction (‘Cholesky’ FAVAR)

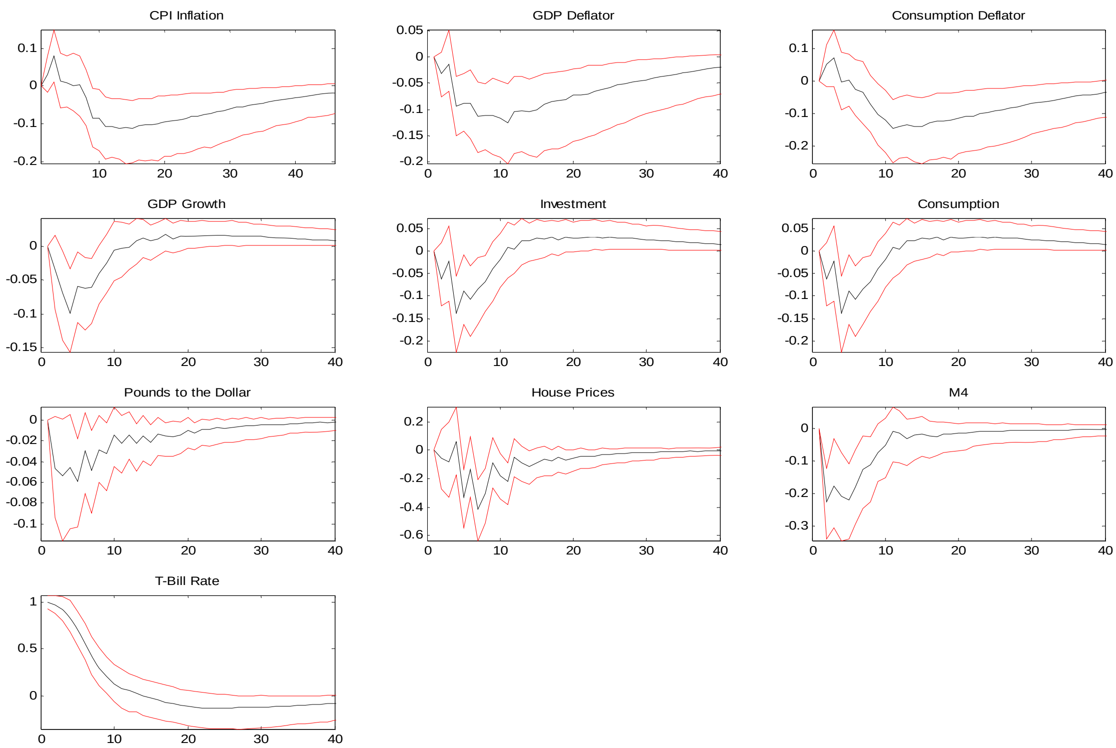

Chart 3: Factors in 'Cholesky' FAVAR

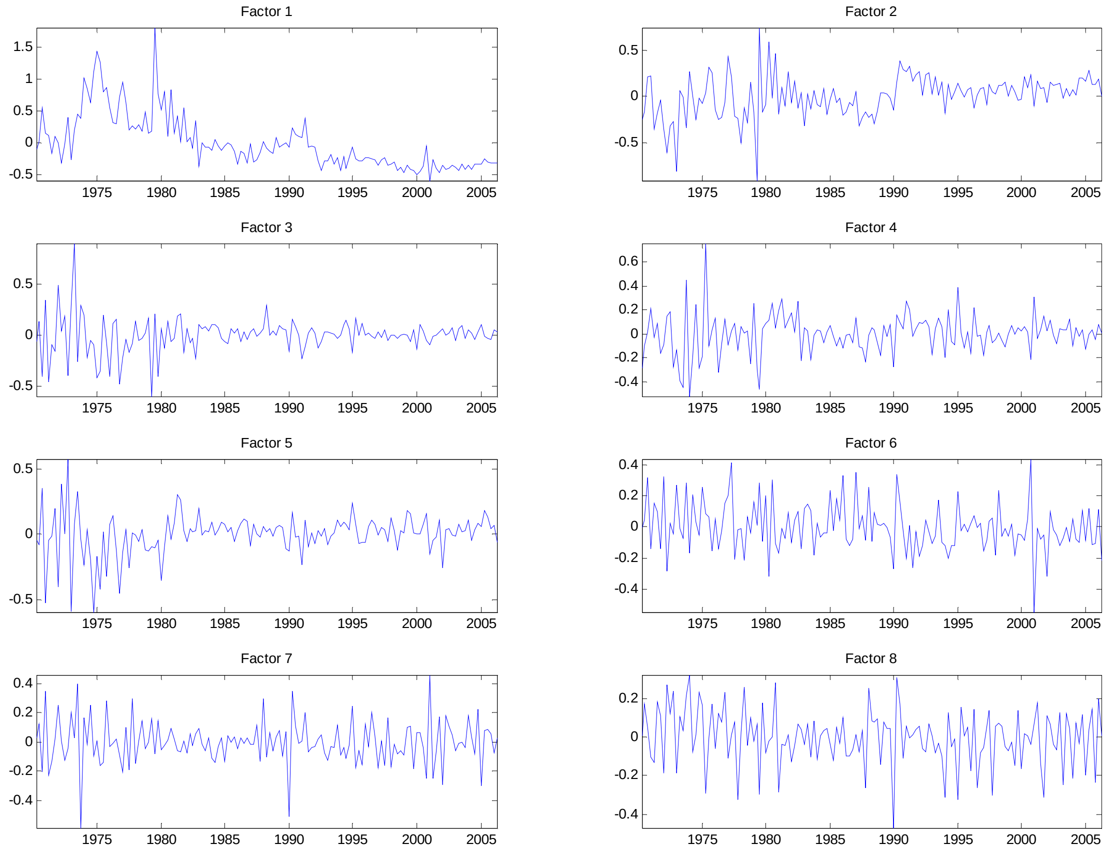

Chart 4: Factors in 'sign-restriction' FAVAR

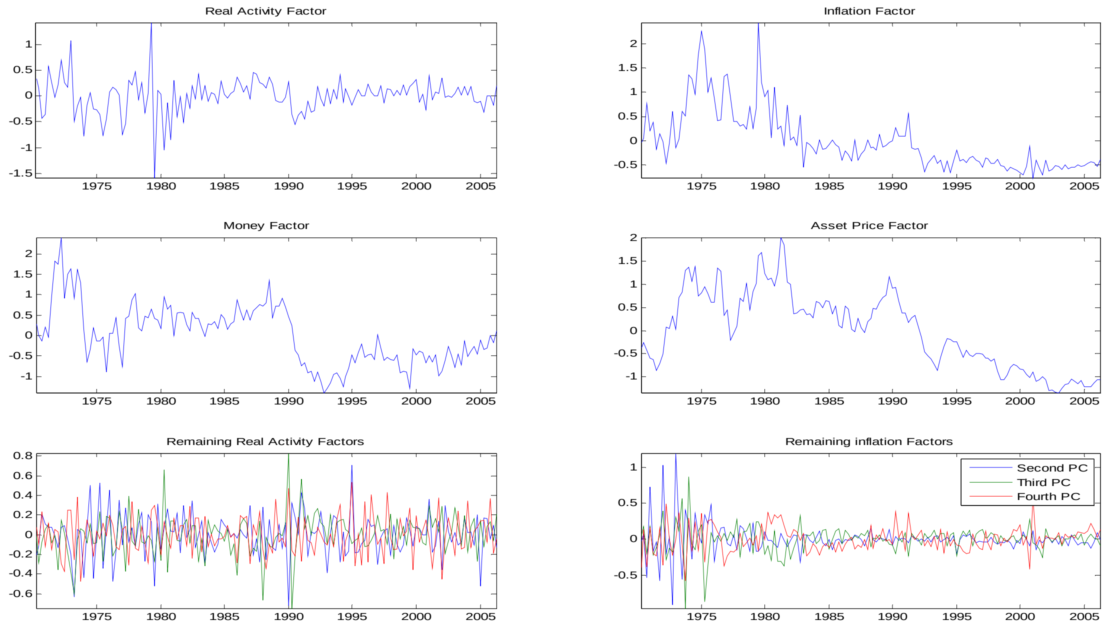

Table A: Sign restrictions used to identify FAVAR[a]

	Demand shock	Supply shock	Monetary policy shock
Output factor	+	+	-
Inflation factor	+	-	-
Money factor	+	*n.a.*	-
Asset price factor	+	*n.a.*	-
Interest rate	+	*n.a.*	+

(a) Shocks correspond to increases in variables, eg an increase in demand, an increase in monetary policy rates.

Chart 5: Impulse responses of key variables to a monetary contraction ('sign-restriction' FAVAR)

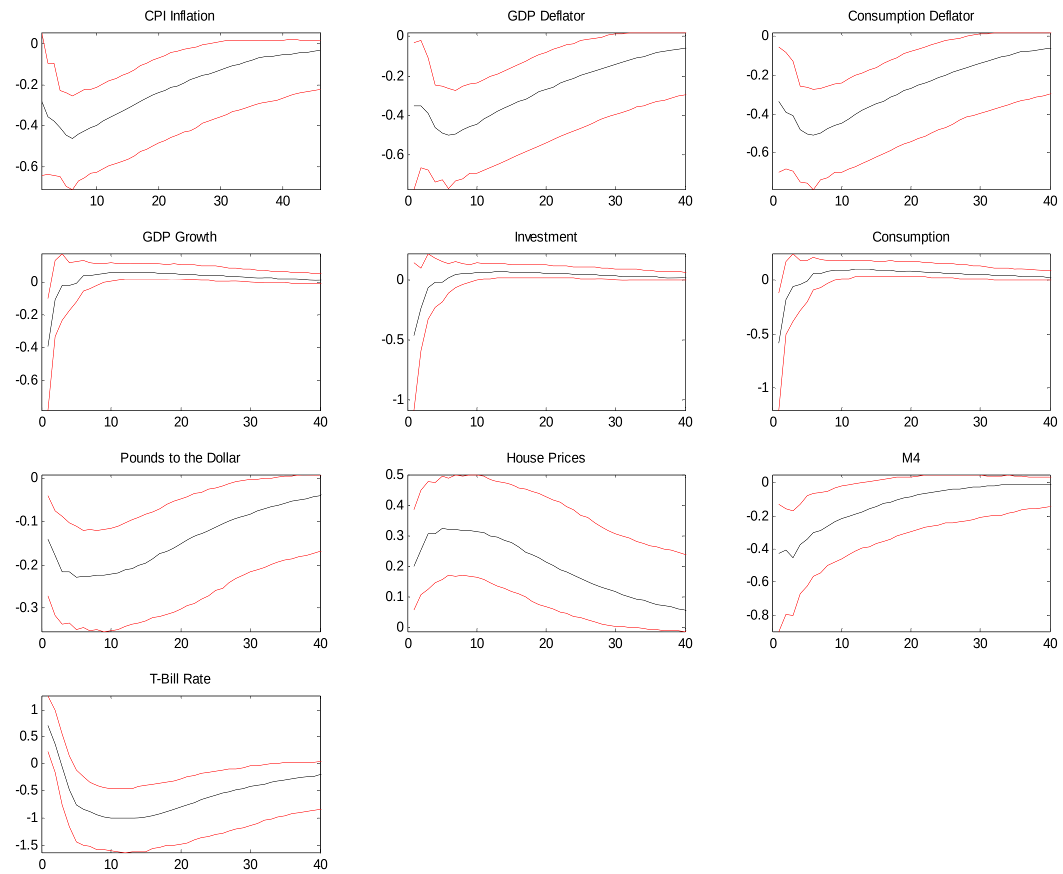

Chart 6: Impulse responses of key variables to a negative supply shock in ‘sign-restriction’ FAVAR

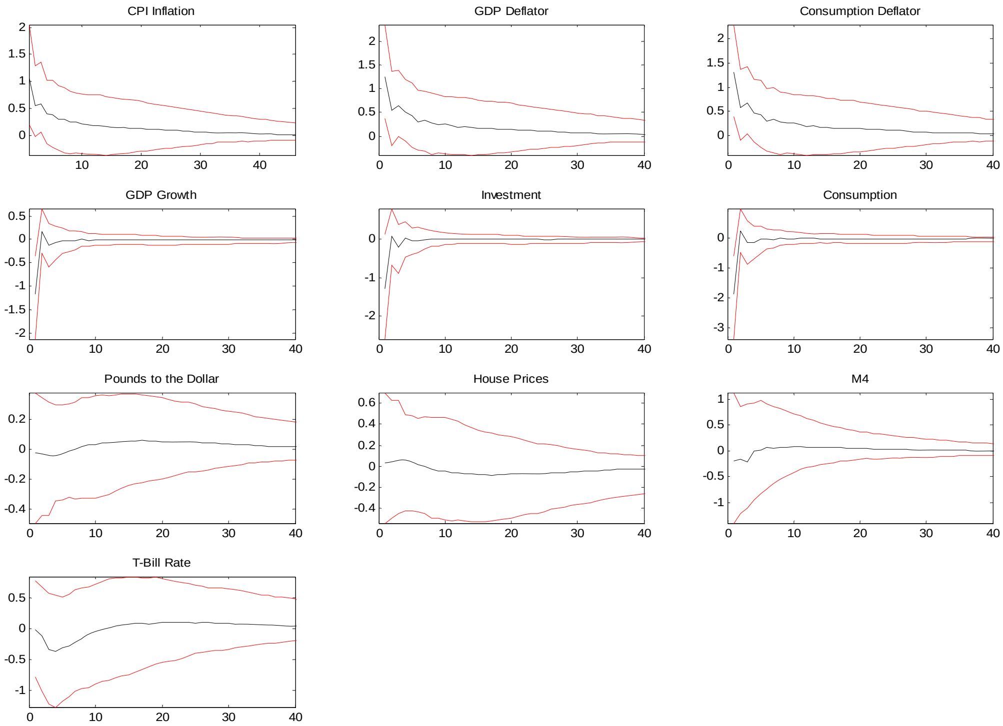

Chart 7: Impulse responses of key variables to a positive demand shock in ‘sign-restriction’ FAVAR

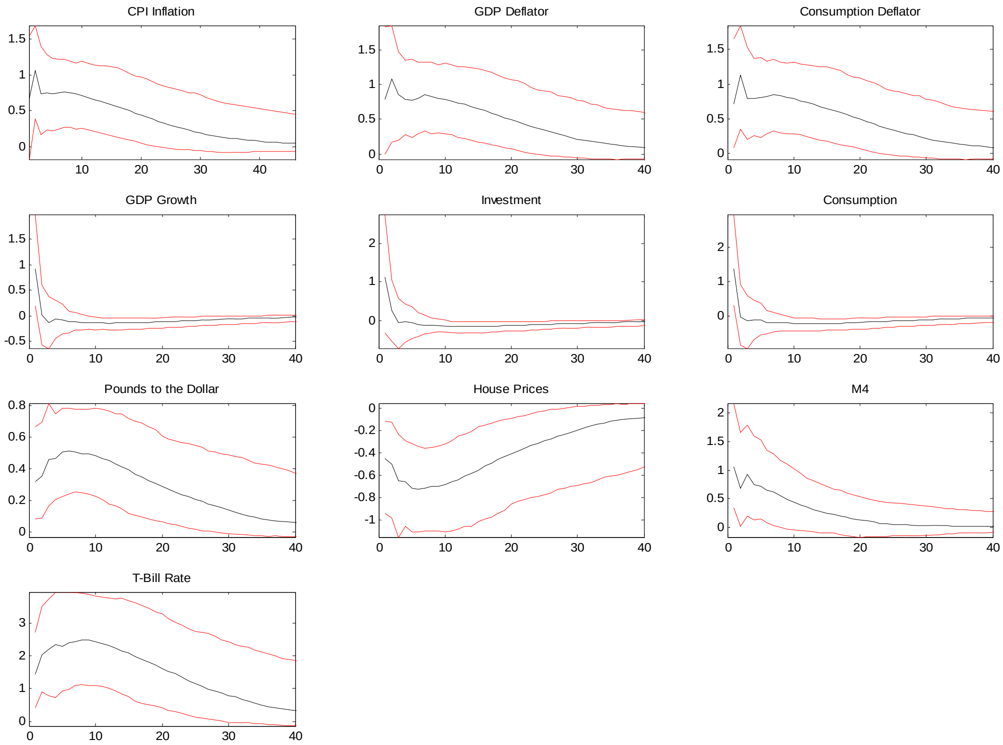

Chart 8: Impulse responses to a contractionary monetary policy shock in 'Cholesky' FAVAR with a structural break in 1993 Q1

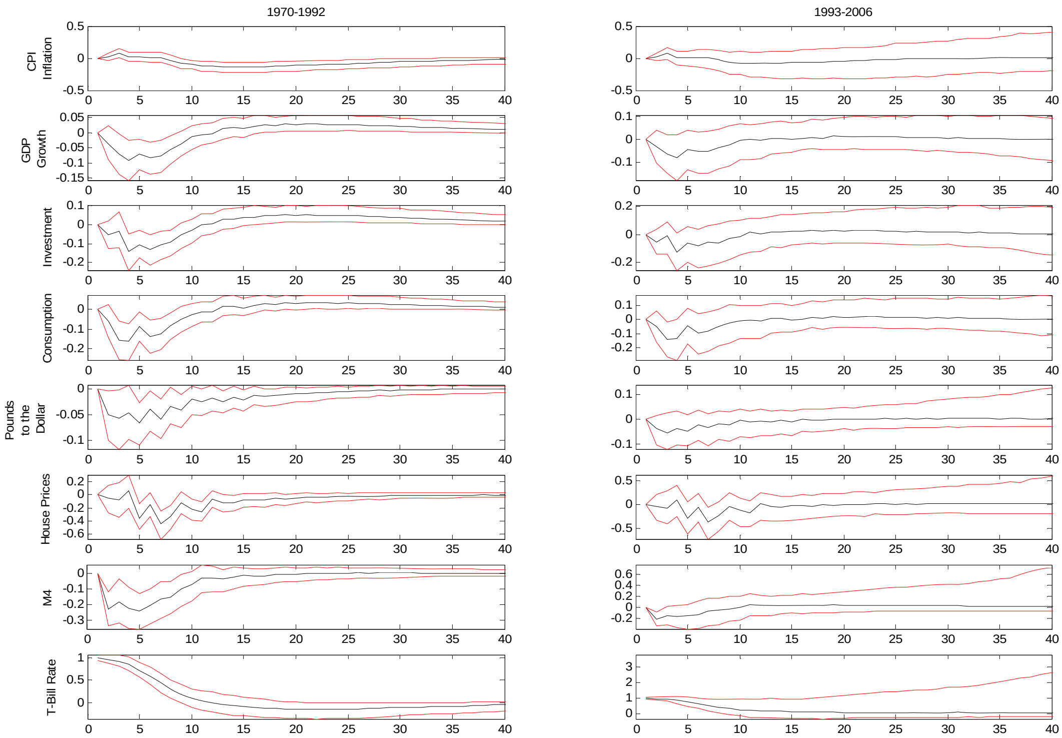

Chart 9: Impulse responses of disaggregated inflation rates and price levels to a monetary contraction ('Cholesky' FAVAR)

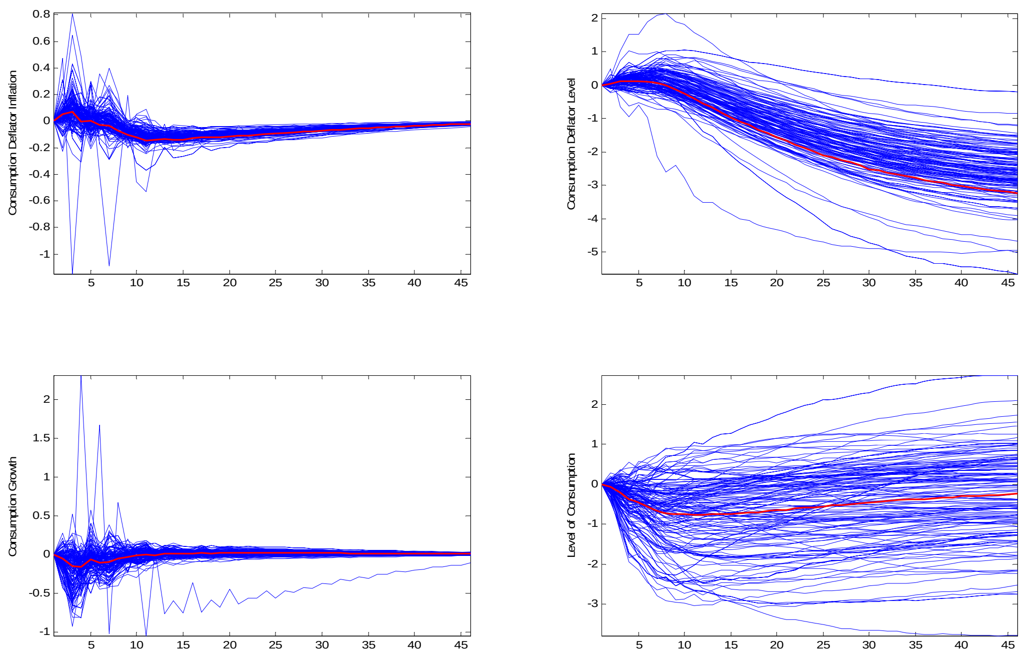

Chart 10: Response of disaggregated prices to a monetary contraction (Cholesky decomposition)

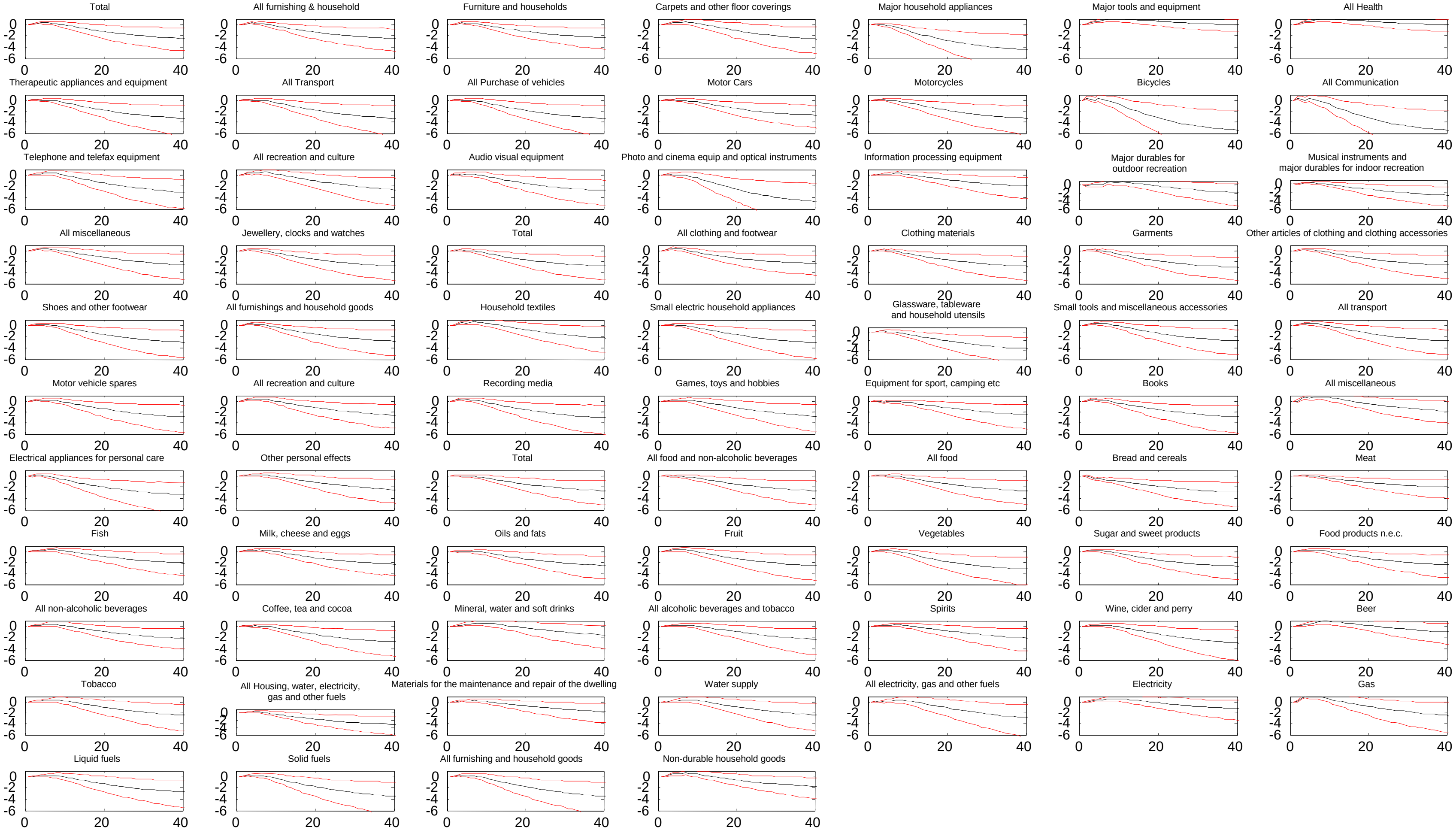

Chart 11: Response of disaggregated prices to a monetary contraction (Cholesky decomposition) continued

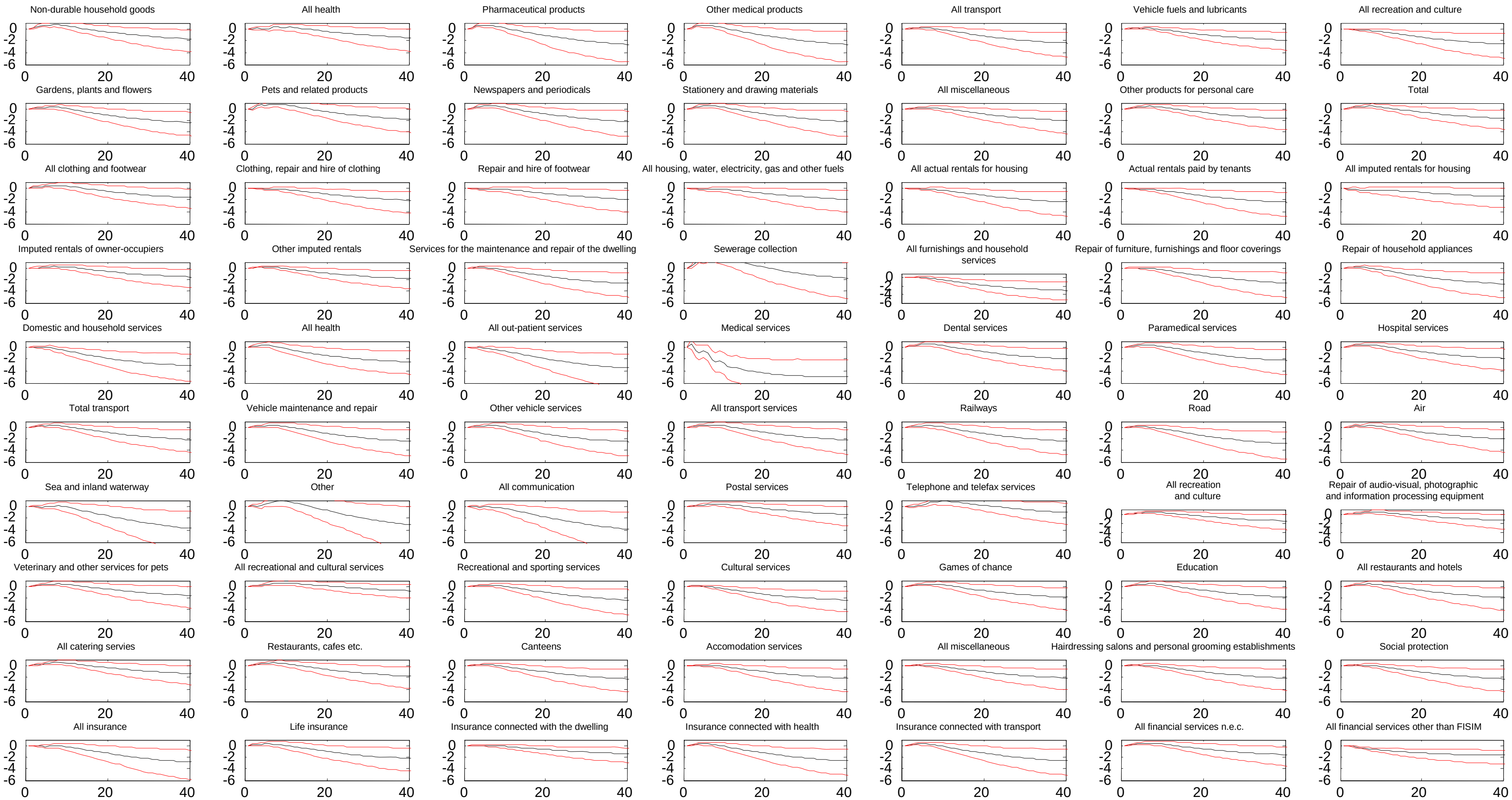

Chart 12: Impulse responses of disaggregated inflation rates and price levels to a monetary contraction ('sign-restriction' FAVAR)

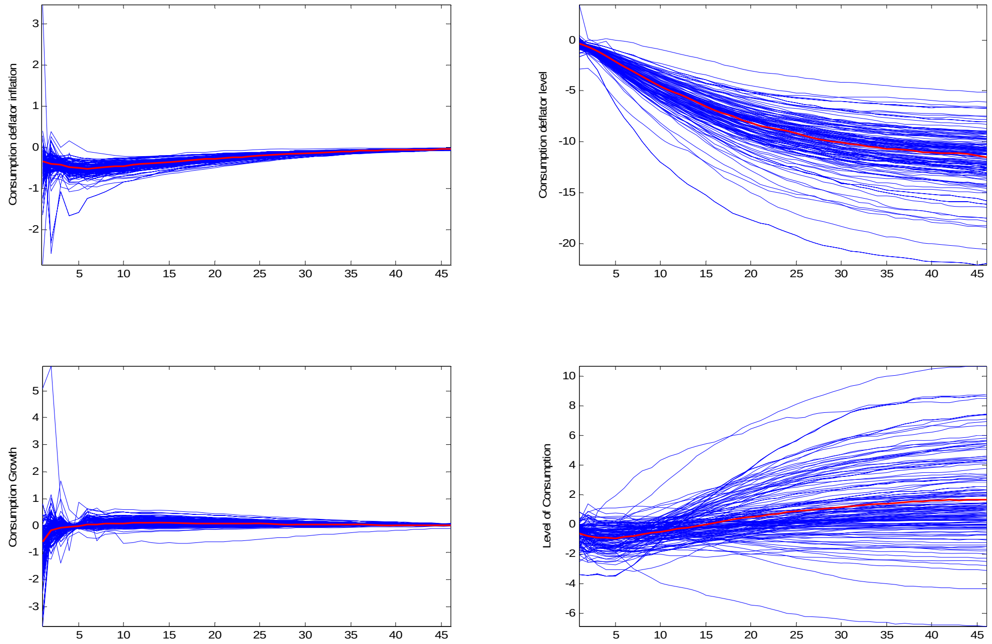

Chart 13: Response of disaggregated prices to a monetary policy shock (sign restrictions)

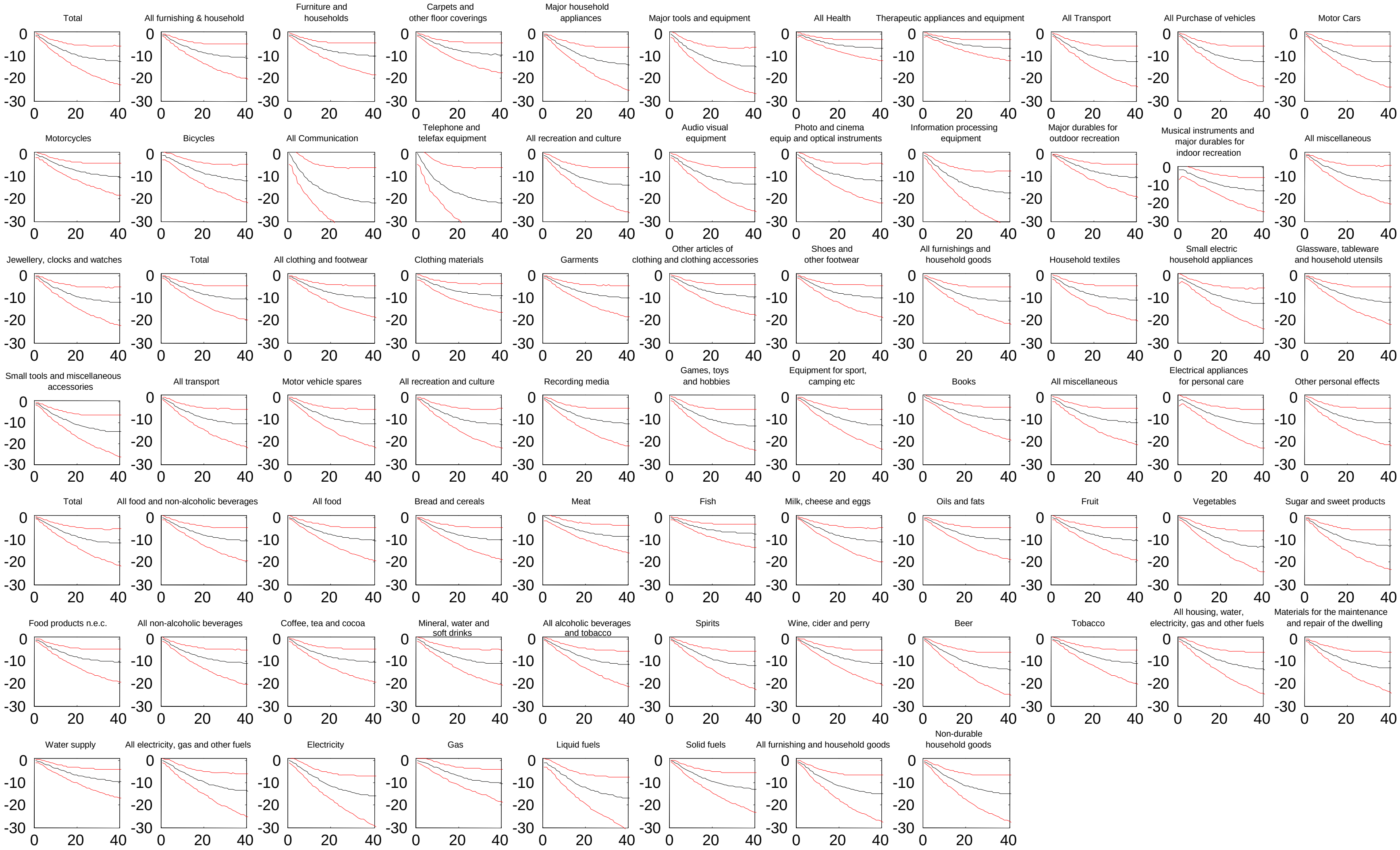

Chart 14: Response of disaggregated prices to a monetary policy shock (sign restrictions) continued

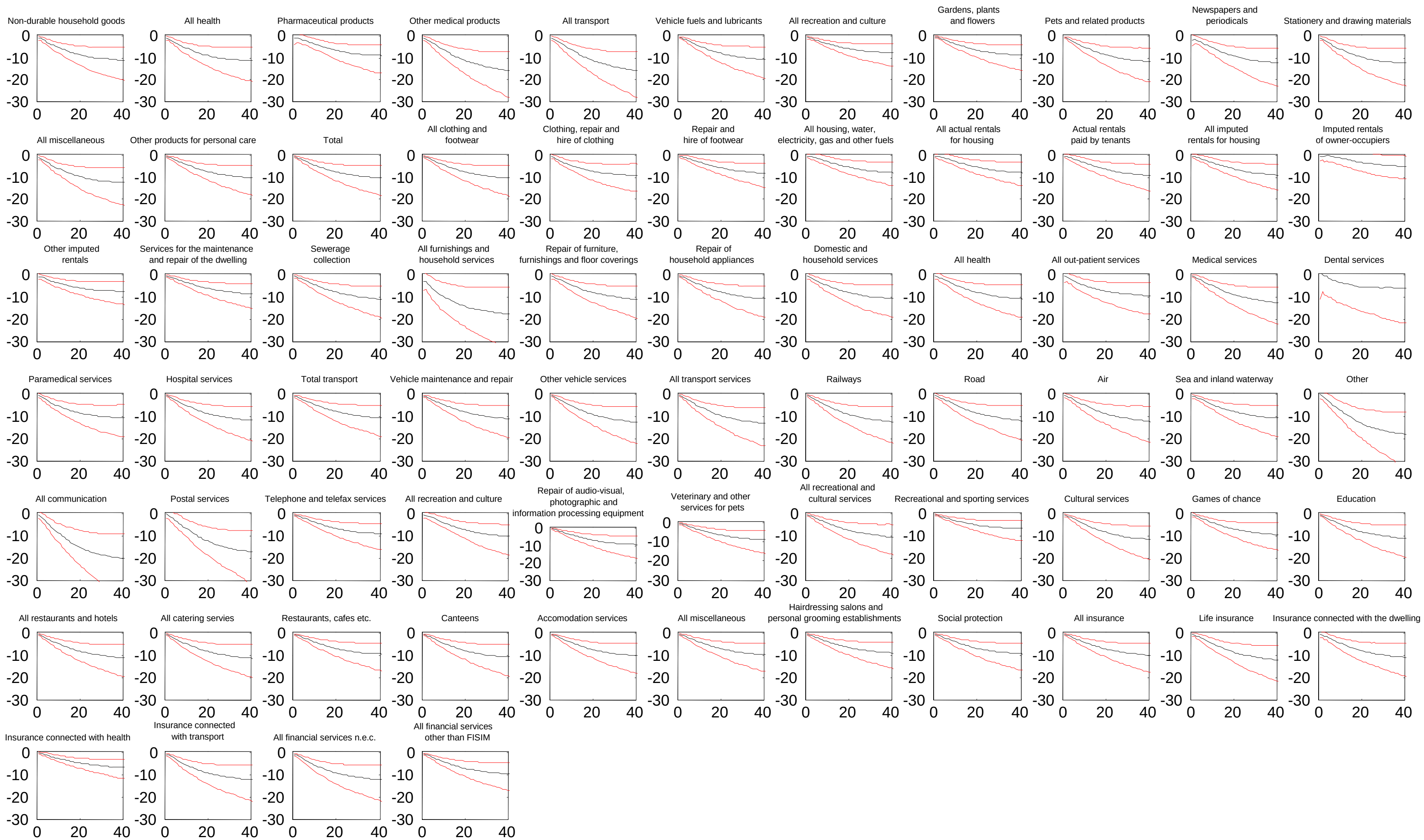

Chart 15: Proportion of sectoral monetary responses different from average inflation ('Cholesky' FAVAR)

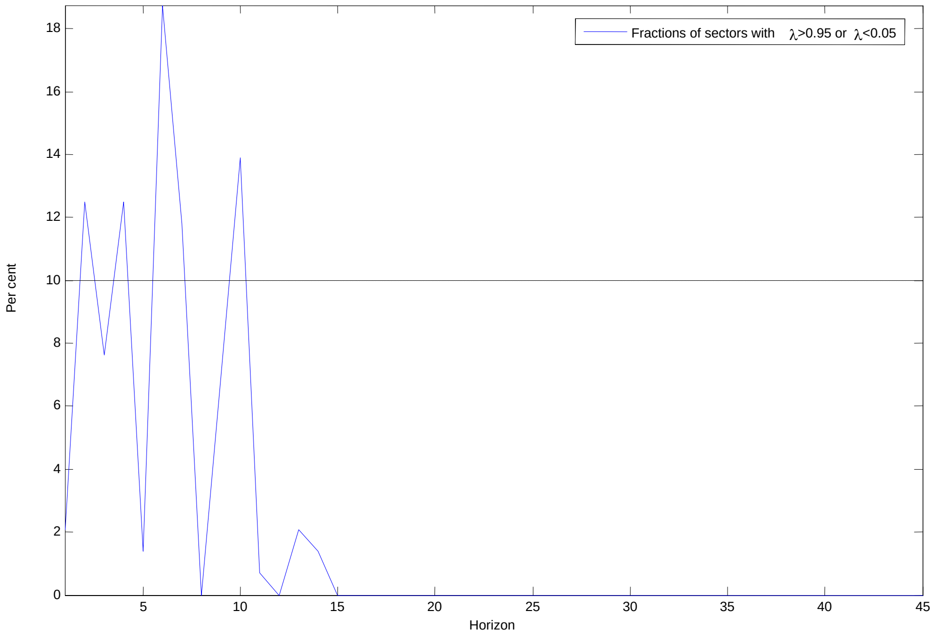

Chart 16: Proportion of sectoral monetary responses different from average inflation ('sign-restriction' FAVAR)

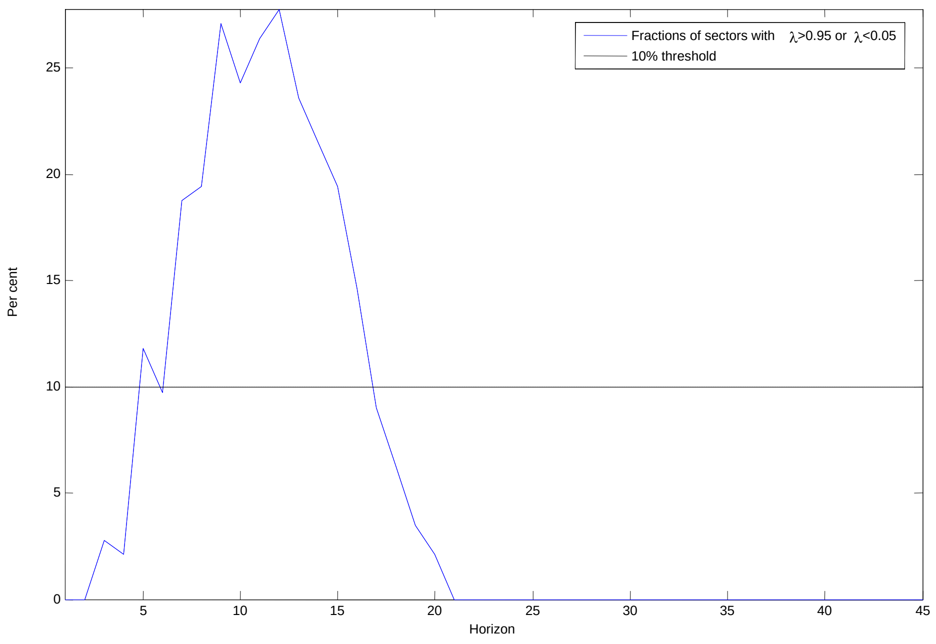

Chart 17: Disaggregated impulse responses to a contractionary supply shock ('sign-restriction' FAVAR)

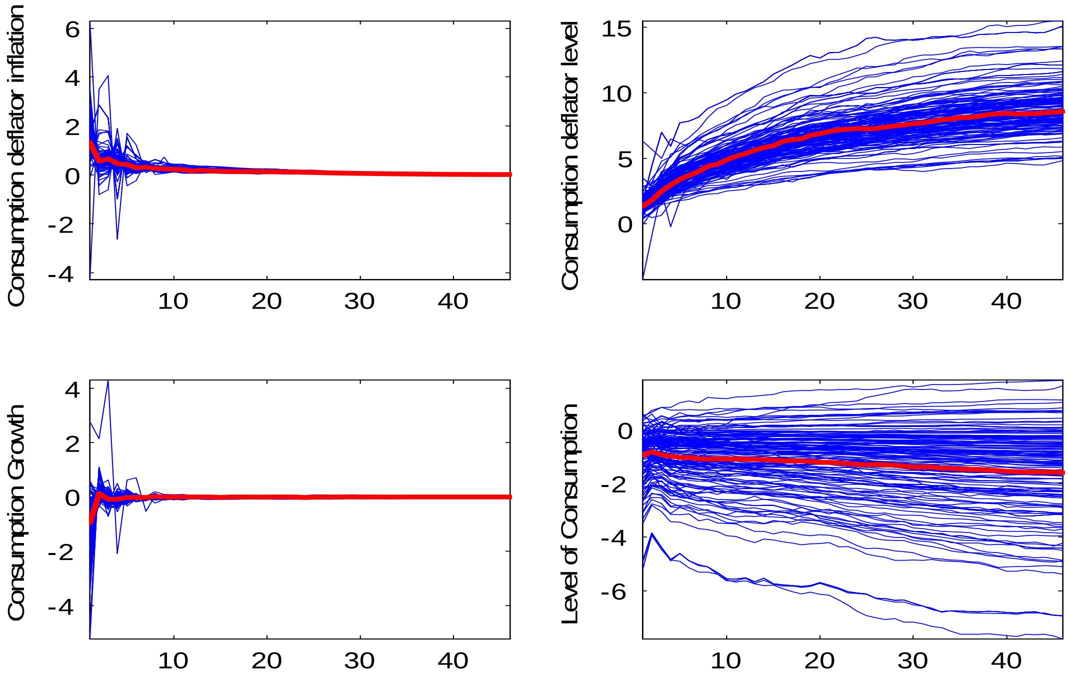

Chart 18: Disaggregated impulse responses to a positive demand shock ('sign-restriction' FAVAR)

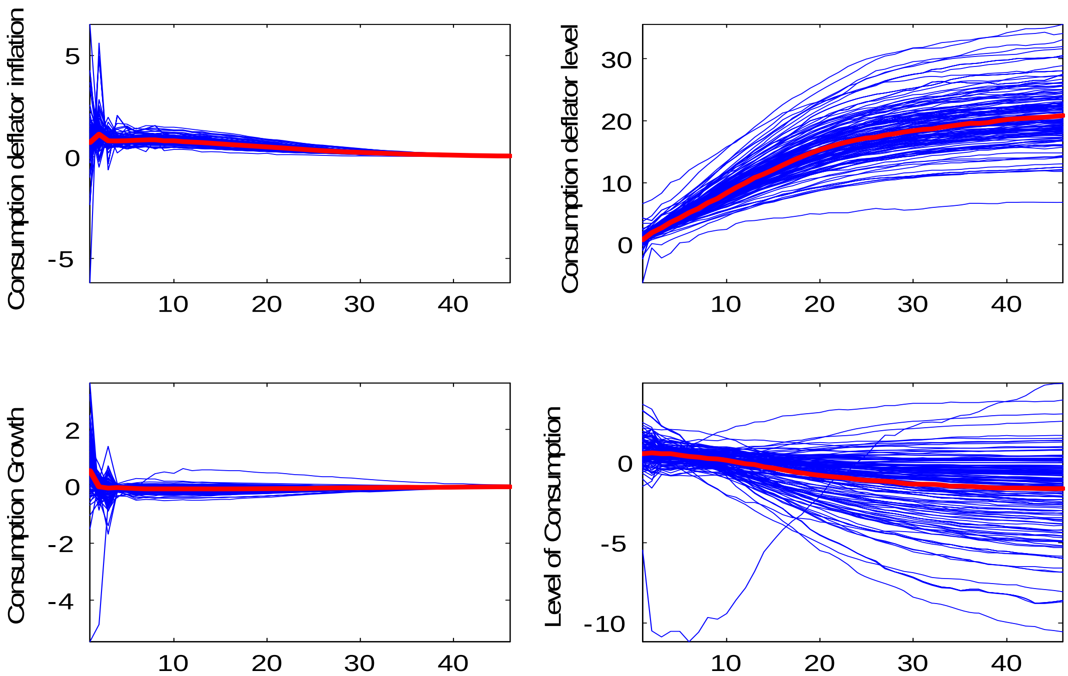

Table B: Volatility and persistence of inflation series ('Cholesky' FAVAR)

	Standard deviation of: Common component	Sector-specific component	R^2	*Persistence of:* Series	Common component	Sector-specific component
Selected aggregate series						
CPI	0.900	0.437	0.809	0.800	0.873	-0.006
GDP deflator	0.886	0.465	0.784	0.691	0.852	-0.201
RPI	0.866	0.500	0.750	0.629	0.810	-0.043
Consumption deflator (PC)	0.977	0.212	0.955	0.770	0.822	-0.081
Wages	0.756	0.654	0.572	0.637	0.866	0.097
Disaggregate PC series						
Unweighted average	0.692	0.690	0.501	0.229	0.473	-0.050
Median	0.723	0.690	0.523	0.304	0.549	-0.046
Minimum	0.263	0.307	0.069	-0.508	-0.398	-0.545
Maximum	0.952	0.965	0.906	0.703	0.854	0.609
Standard deviation	*0.153*	*0.150*	*0.202*	*0.298*	*0.274*	*0.200*

Table C: Volatility and persistence of inflation series ('sign-restriction' FAVAR)

	Standard deviation of: Common component	Sector-specific component	R^2	*Persistence of:* Series	Common component	Sector-specific component
Selected aggregate series						
CPI	0.862	0.506	0.744	0.800	0.826	-0.209
GDP deflator	0.891	0.453	0.794	0.691	0.810	-0.232
RPI	0.883	0.469	0.780	0.629	0.835	-0.085
Consumption deflator (PC)	0.980	0.201	0.960	0.770	0.840	-0.069
Wages	0.650	0.760	0.423	0.637	0.826	0.197
Disaggregate PC series						
Unweighted average	0.683	0.698	0.491	0.229	0.500	-0.048
Median	0.708	0.706	0.502	0.304	0.582	-0.041
Minimum	0.215	0.306	0.046	-0.508	-0.421	-0.441
Maximum	0.952	0.977	0.907	0.703	0.845	0.529
Standard deviation	*0.158*	*0.150*	*0.204*	*0.298*	*0.298*	*0.191*

Table D: Correlations between sector-specific factors and monetary policy responses

	Accumulated impulse response		
	10 quarters	20 quarters	40 quarters
Cholesky FAVAR			
Variance of sector-specific factors	0.136	0.158*	0.158*
Persistence of sector-specific factors	0.110	0.189**	0.209**
Sign-restriction FAVAR			
Variance of sector-specific factors	0.183**	0.154*	0.136
Persistence of sector-specific factors	0.161*	0.166**	0.164**

* indicates significance at the 10% level
** indicates significance at the 5% level

Chart 19: Correlation between monetary policy response and the variance of sector-specific factors ('sign-restriction' FAVAR)

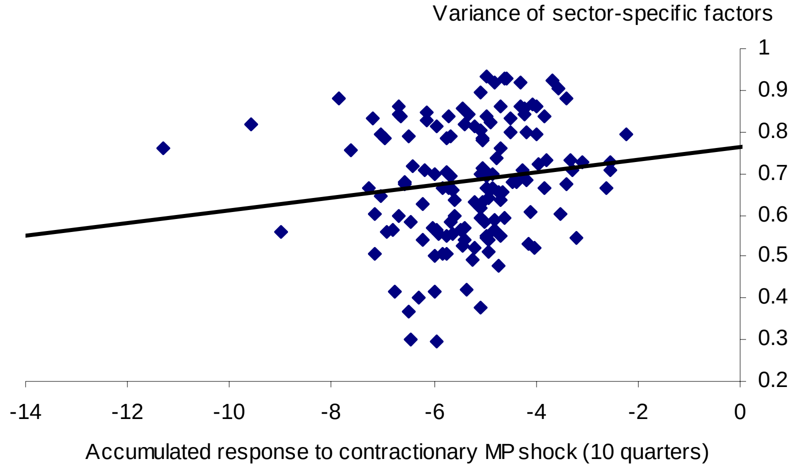

Table E: Correlations between sectoral characteristics and model-based results

	Accumulated impulse responses			*Sector-specific factors*	
	10 quarters	20 quarters	40 quarters	Variance	Persistence
Cholesky FAVAR					
Gross profit share	0.228	0.307**	0.294**	-0.071	0.231*
Import intensity	-0.317**	-0.293**	-0.216	-0.151	-0.282**
Concentration ratio (5%)	0.165	0.121	0.073	0.312**	0.136
Concentration ratio (10%)	0.199	0.168	0.125	0.299**	0.158
Sign-restriction FAVAR					
Gross profit share	0.300**	0.213	0.177	-0.081	0.236*
Import intensity	-0.340**	-0.214	-0.189	-0.172	-0.256*
Concentration ratio (5%)	-0.126	-0.200	-0.240*	0.312**	0.070
Concentration ratio (10%)	-0.112	-0.193	-0.238	0.312**	0.080

* indicates significance at the 10% level
** indicates significance at the 5% level

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