On Implications of Micro Price Data for Macro Models*

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Abstract

We review the recent literature that studies new, detailed micro data on prices. We discuss implications of the new micro data for macro models. We argue that the new micro data are helpful for macro models but not decisive. There is no simple mapping from the frequency of price changes in micro data to impulse responses of prices and quantities to shocks. We discuss ideas that promise to deliver macro models matching the impulse responses seen in macro data while being broadly in line with micro data.

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1 Introduction

In his "Handbook of Macroeconomics" chapter written a decade ago, Taylor (1999) took stock of the micro evidence on price and wage setting available at the time. Taylor (1999, p. 1020-1021) summarized the evidence in four points. First, he concluded that studies of micro data did not support the casual observation that prices are changed more frequently than wages. Instead, studies of micro data suggested that price changes and wage changes have about the same average frequency – about one year. Second, Taylor noted that there is a great deal of heterogeneity in price setting and wage setting. Third, he concluded that neither price setting nor wage setting are synchronized. Fourth, Taylor observed that the frequency of price and wage changes depends positively on the average rate of inflation.

Most of the micro evidence on price setting that Taylor (1999) reviewed was based on a relatively narrow set of products such as magazines (Cecchetti, 1986) and goods sold from retail catalogues (Kashyap, 1995). Since the time Taylor wrote economists have gained access to new, detailed micro data on prices. The new micro data include data collected in order to compute consumer and producer price indices in a number of countries as well as scanner data from supermarket chains. In this paper we review the literature that studies the new micro data, thereby revisiting some of Taylor's conclusions.[1] Furthermore, we discuss implications of the new micro data for macro models.

The new micro data confirm that there is a great deal of heterogeneity in price setting, in terms of the frequency and size of price changes, but also in terms of how frequent "sales" are and what form sales take. Despite all the heterogeneity, micro price data show a number of regularities. First, prices remain constant for extended periods of time in many sectors of the economy. Second, prices appear to change less frequently in the euro area than in

[1] The closing sentences of Taylor (1999, p. 1044) call for more research: "Understanding these [staggered price and wage setting] models more thoroughly takes one well beyond macroeconomics into the heart of the price discovery and adjustment process in competitive and imperfectly competitive markets. Further research on the empirical robustness and microeconomic accuracy of staggered contracts models is thus both interesting and practically important."

the United States. The median consumer price lasts about 4-9 months in the U.S. economy, depending on whether price changes related to sales and item substitutions are included or excluded. The median consumer price lasts about 11 months in the euro area. Third, when prices change, on average they change by large amounts relative to inflation. This suggests that idiosyncratic shocks are a much more important cause of variation in prices than aggregate shocks. At the same time, many price changes are small. Fourth, new cross-country evidence confirms that the frequency of price changes depends positively on the average rate of inflation. Fifth, there is indeed little evidence of synchronization of price changes.

One reason why macro modelers are interested in micro price data is that in familiar and tractable macro models the frequency of price changes maps easily into impulse responses of prices and quantities to shocks. The New Keynesian model with Calvo pricing is a case in point. We provide two examples to show that there may be no simple mapping between the frequency of price changes in micro data and the speed of impulse responses of prices and quantities to shocks. The first example involves time series models estimated using sectoral price data, as in Boivin, Giannoni, and Mihov (2007) and Maćkowiak, Moench, and Wiederholt (2008). Both papers find that sectoral price indices respond quickly to sector-specific shocks. In this sense prices are not sticky. At the same time, sectoral price indices respond slowly to macro shocks. In this sense prices are sticky. If the frequency of price changes were decisive for impulse responses, one would expect prices to respond with roughly equal speed to both kinds of shocks. It turns out that in the data the degree of stickiness of prices – defined as the speed of response of prices to shocks – appears to be conditional on the source of the shock. This does not imply that the frequency of price changes is irrelevant. The frequency of price changes helps explain the speed of impulse responses of prices to macro shocks in a cross-section of sectors.

The second example involves the DSGE model of Smets and Wouters (2003). When the Smets-Wouters model is estimated using macro data from, alternatively, the United States and the euro area, the estimated value of the Calvo parameter is somewhat larger for the euro area than for the U.S. The difference is not statistically significant. The slope of the New Keynesian Phillips Curve is estimated to be somewhat lower in the euro area than in the U.S. Therefore, the Smets-Wouters model reflects the notion that prices change less frequently in the euro area compared to the United States, as is apparent from micro data, but the model does so only weakly. Furthermore, the slope of the New Keynesian Phillips Curve is estimated to be very low in both economies. Whether prices change on average every 4 months or every 11 months, nominal rigidity by itself does not suffice to explain the low slope of the New Keynesian Phillips Curve in the Smets-Wouters model.[2] One needs to combine nominal stickiness with a sufficient degree of real rigidity.[3] The impulse responses, and therefore the predictions concerning the effects of macro shocks, depend on the entire DSGE model and all its parameters, not only on the price setting mechanism and the parameter governing the frequency of price changes.

In an ideal world macroeconomists would set up, solve and understand a DSGE model with many heterogeneous firms and households, in which firms and customers in different sectors interact differently, and which matches in detail both micro data and macro data. Realistically all we can hope for, at least for some time, is a model that matches macro data in detail while telling a reasonable story broadly in line with micro data. Recent DSGE models have made progress matching macro data in detail. We survey the recent literature on models of price setting. We search for a story or a set of stories that would simultaneously: (i) imply persistent impulse responses to macro shocks, similar to the impulse responses in the Smets-Wouters model; (ii) be broadly in line with micro price data. We do not think that macroeconomists have developed such a story yet. The most promising lines of research from our point of view involve work with models in which prices can respond quickly and by large amounts to idiosyncratic shocks and, at the same time, prices respond slowly and by small amounts to macro shocks. One line of research with this feature involves models in which a high degree of real rigidity arises conditionally on a macro shock. Another line of research with this feature involves imperfect information about macro shocks. In both lines of research some degree of flexibility at the micro level can potentially coexist with a

[2] Similarly, whether prices change on average every 4 months or every 11 months, nominal rigidity by itself does not suffice to explain why the impulse response of real aggregate output to monetary policy shocks lasts two-three years in structural VAR models. See, for example, Christiano, Eichenbaum, and Evans (1999), Kim (1999), and Leeper, Sims, and Zha (1996).

[3] The concept of real rigidity is due to Ball and Romer (1990).

sizable amount of stickiness at the macro level. Both lines of research, or some combination of them, may eventually be capable of producing a DSGE model that fits macro data as well as (or better than) the Smets-Wouters model while providing a reasonable story broadly in line with micro price data.

Section 2 of this paper reviews the recent literature that studies new, detailed micro data on prices. In Section 3 we discuss the recent literature that compares standard models of price setting used in macroeconomics to the new micro data. In Section 4 we argue that there is no simple mapping from the frequency of price changes in micro data to impulse responses of prices and quantities to shocks. In Section 5 we discuss promising lines of research. Concluding remarks are in Section 6.

2 "What do the new micro data say?"

In this section we review the recent literature that studies new, detailed micro data on prices from the United States, the euro area and other countries. We begin by discussing the literature that studies U.S. data. Afterwards we discuss the literature that studies euro area data and we summarize new cross-country evidence. At the end of this section we discuss some of the evidence on causes of price rigidity from surveys of firms from the U.S. and the euro area.

2.1 Micro price data in the United States

The micro data underlying the consumer price index in the United States are so rich that questions of the form "what do the micro data say?" have no simple answers. The question "how frequently do prices change?" has no simple answer, because in micro data there is a distribution of the frequency of price changes. Klenow and Kryvtsov (2007) and Nakamura and Steinsson (2007a) study the CPI Research Database provided by the Bureau of Labor Statistics. The CPI Research Database contains the non-shelter component of the data collected by the BLS in order to compute the CPI. The CPI Research Database covers all goods and services other than shelter, or about 70 percent of the CPI. The BLS divides goods and services into about 300 Entry Level Items, or ELIs. The BLS collects prices monthly for all products in the three largest metropolitan areas (New York, Los Angeles, and Chicago). The BLS also collects prices monthly for food and fuel products in all areas. The BLS collects prices for other products and other areas only bimonthly. Klenow and Kryvtsov (2007) and Nakamura and Steinsson (2007a) focus on prices collected monthly. The CPI Research Database begins in January 1988. Klenow and Kryvtsov use the data in the CPI Research Database through January 2005. Nakamura and Steinsson focus on the data from 1998.[4] Figure 1 shows the distribution of the frequency of price changes for ELIs from Nakamura and Steinsson (2007a). It is striking how dispersed the distribution is. The ELI with the lowest frequency of price changes, 1.6 percent, is "Legal Services". Only 1.6 percent of prices in the category "Legal Services" change on average from month to month. The ELI with the highest frequency of price changes, 100 percent, is "Used Cars". All prices in this category change from month to month.[5]

[Insert Figure 1]

Table 1 illustrates in another way the heterogeneity in the frequency of price changes. Table 1 reports the distribution of the frequency of price changes for so called Major Groups. Major Groups are fairly broad sub-baskets of the CPI basket. The median frequency of price changes for Major Groups ranges from 6.6 percent for "Services Excluding Travel" to 87.6 percent for "Vehicle Fuel".[6]

[Insert Table 1]

Klenow and Kryvtsov (2007) estimate the median frequency of price changes between 1988 and 2004 to be 27.3 percent. The implied median price duration is the inverse of this number, 3.7 months. This means that half of all prices in the U.S. economy last less than 3.7 months.[7] Klenow and Kryvtsov estimate the mean frequency of price changes between 1988 and 2004 to be 36.2 percent. One can understand why the mean is higher than the median by noting in Figure 1 that there are a few ELIs for which price changes are very

[4] The BLS revised the ELI structure in 1998. Prior to 1998 there were about 360 ELIs. Since 1998 there are about 270 ELIs.

[5] Figure 1 is based on Table 17 in the supplement to Nakamura and Steinsson (2007a) entitled "More Facts About Prices".

[6] Table 1 is based on Table 2 in Nakamura and Steinsson (2007a).

[7] Bils and Klenow (2004) report the median price duration of 4.3 months. Bils and Klenow's estimate is based on summary statistics from the BLS for the period 1995 to 1997.

frequent. The implied mean price duration is 6.8 months.

What does the heterogeneity in the frequency of price changes imply for macro models? In macro models we almost always use the convenient assumption of a representative firm (or many homogenous firms). The new micro data show that in the real world there are many heterogenous firms and there is no "representative firm". In general, we cannot expect a macro model with many heterogenous firms to behave like a macro model with a "representative firm". One possible way forward for macro modelers is to construct a model with a representative firm and compare selected predictions of this model to a version of the same model with many heterogenous firms. One can calibrate the representative-firm-model so that its selected predictions come close to the version of the model with many heterogenous firms. Afterwards, one can have more trust in other predictions of the representative-firm-model. This may be wishful thinking because no representative-firm-model may come close to the model with many heterogenous firms. Furthermore, conclusions from this kind of analysis will be model-specific. Note also that the heterogeneity in the frequency of price changes is only one form of the heterogeneity present in micro price data. Even a model that takes into account fully the heterogeneity in the frequency of price changes will, in general, neglect other forms of heterogeneity in price setting behavior. Carvalho (2006) and Nakamura and Steinsson (2007b) are examples of recent papers introducing heterogeneity in price setting behavior into macro models.

The answer to the question "how frequently do prices change?" is complicated further by the presence of "sales" and "forced item substitutions" in micro price data. BLS employees who visit retail outlets in order to collect data on prices record certain prices as "sale" prices.[8] Klenow and Kryvtsov (2007) report that about 11 percent of price quotes in their data are sale prices. "Forced item substitutions" occur when an item in the sample has been discontinued from an outlet and the BLS employee records the price of a similar replacement item in the outlet. This often takes the form of a product upgrade or model changeover and about 80 percent of the time involves a price change. The monthly rate of forced item substitutions is about 3 percent. So far we have reported the frequency of

[8] According to the BLS, a "sale" price is (a) temporarily lower than the "regular" price; (b) available to all consumers; and (c) usually identified by a sign or statement on the price tag.

price changes based on all posted prices. It turns out that the answer to the question "how frequently do prices change?" depends to a considerable degree on whether one excludes price changes related to sales and forced item substitutions and how exactly one goes about doing this. Nakamura and Steinsson (2007a) estimate that, after removing sales and forced item substitutions from the data, the median price duration rises to 8-11 months. Klenow and Kryvtsov (2007) emphasize that this estimate is obtained after a lot of filtering of the data. Klenow and Kryvtsov find that looking only at "regular" prices, i.e. removing all sale-related price changes from the data, raises the estimated median price duration to 7.2 months from 3.7 months.[9] Next, removing all forced item substitutions from the data increases the estimated median price duration to 8.7 months. Then looking only at adjacent prices raises the estimated median price duration further to 9.3 months. Note that this is an estimate one obtains when looking only at consecutive monthly regular prices in between forced item substitutions.[10]

Nakamura and Steinsson (2007a) observe that sale-related price changes are different from regular price changes. For example, sale-related price changes are larger and more transient than regular price changes. Klenow and Kryvtsov (2007) point out that a sale price is more likely to differ from the previous sale price than a regular price is to differ from the previous regular price. Sales are stochastic; they are not a fixed discount from the regular price. Matters are complicated yet further by the fact that sales and forced item substitutions are important in some sectors but not in others, and firms operating in different sectors have different kinds of sales. Nakamura and Steinsson (2007a) emphasize the heterogeneity in the prevalence of sales and forced item substitutions across Major Groups. For example, 87 percent of price changes in "Apparel", 67 percent of price changes in "Household Furnishings", and 58 percent of price changes in "Processed Food" are sale-related price changes. The monthly rate of forced item substitutions is about 10 percent in "Apparel" and "Transportation Goods" and about 6 percent in "Recreation Groups".

[9] Removing all sale-related price changes from the data raises the estimated mean price duration to 8.6 months from 6.8 months. The estimated median frequency of price changes falls to 13.9 percent from 27.3 percent. The estimated mean frequency of price changes falls to 29.9 percent from 36.2 percent. See Table 1 in Klenow and Kryvtsov (2007).

[10] See Table 2 in Klenow and Kryvtsov (2007).

"Utilities", "Vehicles Fuel", "Travel", and "Services Excluding Travel" are sectors of the economy in which the fraction of sale-related price changes is close to zero. And there are sectors of the economy in which the monthly rate of forced item substitutions is close to zero: "Vehicles Fuel" and "Utilities", for example.[11] Klenow and Kryvtsov (2007) report that about 60 percent of sales are associated with a V-shape in a price quote, as the price goes down and after some time returns to the same pre-sale regular price. The other common type of a sale is a clearance sale, often associated with repeated markdowns. Clearance sales occur frequently in the Major Group "Apparel", sometimes in the Major Groups "Household Furnishings" and "Recreation Groups", and almost never in other Major Groups.[12]

What does the presence of sales and forced item substitutions in micro price data imply for macro models? An optimizing model of sales will in general predict that the magnitude, frequency and duration of sales respond to macro shocks. Products are likely to sell at bigger discounts and be marked down more frequently and for longer time spans when aggregate productivity is growing quickly. Holding the prior "exclude all sale-related price changes from macro models" may therefore be unjustified. Klenow and Willis (2007) estimate that sale-related price changes in the BLS data are at least as sensitive to inflation as are regular price changes. Furthermore, even if sales are caused by shocks orthogonal to the macro economy, the presence of sales may matter for the response of prices to macro shocks. In the rational inattention model of Maćkowiak and Wiederholt (2008) idiosyncratic uncertainty faced by firms matters for the response of prices to macro shocks. As far as forced item substitutions are concerned, it seems reasonable to assume that product turnover is not caused by a desire for a price change. However, we find it intuitive that macro shocks play a role in a firm's decision whether to use product turnover as a repricing opportunity or not, whatever the reasons behind product turnover. Macro shocks may also influence the timing and the frequency of product turnover. Isn't it a good idea to replace old products with new ones when the aggregate economy is strong? Klenow and Willis (2007) estimate that price changes associated with forced item substitutions in the BLS data are sensitive to inflation.[13]

[11] See Table 2 and Table 5 in Nakamura and Steinsson (2007a).

[12] See Table 7 in the supplement to Nakamura and Steinsson (2007a) entitled "More Facts About Prices".

[13] We do not mean to suggest that the findings of Klenow and Willis (2007) close the debate on whether sales and forced item substitutions respond to macro shocks. The findings of Klenow and Willis (2007)

Kehoe and Midrigan (2007) is a recent paper incorporating V-shape sales into a menu cost model. Kehoe and Midrigan find that in the menu cost model with sales nominal shocks have significantly larger real effects compared to the same model without sales calibrated to all posted prices. The reason is that sale-related price changes are transient and therefore do not offer firms much of an opportunity to respond to persistent nominal shocks.

Bils and Klenow (2004) analyze determinants of the frequency of price changes. Bils and Klenow find that products sold in competitive markets, as measured by concentration ratios or wholesale markups, display more frequent price changes. However, this results disappears once Bils and Klenow control for a good being energy-related or a fresh food. In Section 2.2 we discuss the determinants of the frequency of price changes using evidence from the euro area.

We have argued that the question "how frequently do prices change?" has no simple answer. The question "by how much do prices change?" has no simple answer either. In micro data there is a distribution of the size of price changes. It turns out that this distribution has fat tails. A typical price change is large and many price changes are small. Klenow and Kryvtsov (2007) find that conditional on a price change the median absolute size of the price change is 11.5 percent. When sale-related price changes are excluded, the median absolute size of the price change falls somewhat to 9.7 percent.[14] Note that the average monthly inflation rate in the sample period of Klenow and Kryvtsov was 0.2 percent. This means that, even excluding sale-related price changes, price changes are on average large relative to inflation. At the same time, small price changes are common. About 44 percent of price changes excluding sales are smaller than 5 percent in absolute value, 25 percent are smaller than 2.5 percent, and 12 percent are smaller than 1 percent.

Nakamura and Steinsson (2007a) document the heterogeneity with respect to the size of price changes across Major Groups. The median absolute size of price changes ranges from about 6 percent in "Utilities" and "Vehicle Fuel" to about 30 percent in "Apparel", "Unprocessed Food" and "Processed Food". Note that price changes in all Major Groups are on average large relative to inflation. After excluding sale-related price changes, the

depend to some degree on their modeling assumptions.

[14] Price increases are 2-3 percentage points smaller on average than price decreases. Both price increases and price decreases are common.

median absolute size of price changes in "Apparel", "Unprocessed Food" and "Processed Food" falls but remains large (12-14 percent) relative to inflation.

Nakamura and Steinsson (2007a) study the micro data underlying the producer price index in the United States. Producer goods can be divided into three groups based on stages of processing: finished goods, intermediate goods, and crude materials. Nakamura and Steinsson estimate the median price duration of finished goods between 1998 and 2005 to be 8.7 months. Nakamura and Steinsson's estimate of the median price duration of intermediate goods is 7 months. Crude materials have almost perfectly flexible prices, the estimated median price duration being 0.2 months. These estimates are based on data excluding forced item substitutions. The frequency of forced item substitutions varies across PPI Major Groups from 0 percent in "Farm Products" to 16.6 percent in "Transportation Goods". Sales are very rare in the PPI data.[15] As in the case of consumer prices, there is a large amount of heterogeneity across PPI Major Groups with respect to the frequency of price changes.[16] Nakamura and Steinsson estimate the median absolute size of price changes for finished producer goods to be 7.7 percent.

Nakamura and Steinsson (2007a) note that interpreting PPI data is difficult. PPI data are collected by the BLS by means of a survey of firms.[17] This gives rise to the concern that firms report "list" prices rather than transaction prices. The BLS attempts to address this concern by requesting prices of actual shipments. Furthermore, many prices collected in order to compile the PPI are likely to be part of explicit or implicit contracts. This raises the possibility that Barro's (1977) criticism applies to some degree and many observed producer prices do not map easily into allocations. An observed price differs from the actual price faced by the buyer, and this actual price is unobserved to researchers. A related point made by Nakamura and Steinsson is that in wholesale markets suppliers may vary quality margins, such as delivery lags, instead of changing the price. We suspect that a version

[15] Unlike the CPI database, the PPI database does not record certain prices as "sale" prices. Nakamura and Steinsson (2007a) use sales filters to assess the importance of sales in the PPI data. The sales filter identify very few sales.

[16] See Table 7 in Nakamura and Steinsson (2007a).

[17] In contrast, BLS employees who collect prices used to compile the CPI record prices of goods actually "on the shelf".

of Barro's criticism applies also to consumer prices in some sectors. Repeated interactions arise also in some sectors of the retail economy. For example, long-term relationships could play a role in explaining why the ELI with the lowest frequency of price changes turns out to be "Legal Services". Furthermore, suppliers may vary quality margins also in retail markets. For example, consumers sometimes must wait in order to purchase a good at a published price. The unobserved cost of waiting affects the shadow price of the good to the consumer.[18] For these reasons, it may be wise to think of the available estimates of the frequency of consumer price changes as lower bounds.

A number of recent papers analyze scanner data from supermarket chains. Scanner datasets include data on quantities in addition to data on prices, and sometimes they also include data on costs. Furthermore, typically scanner data have weekly frequency. This means that fewer price changes are "missed" compared with monthly data from national statistical authorities. On the other hand, scanner data are not as representative as data from national statistical authorities. Eichenbaum, Jaimovich and Rebelo (2008) study a new weekly scanner dataset from a major U.S. retailer that contains information on prices, quantities, and costs for over 1000 stores. Eichenbaum, Jaimovich and Rebelo find that prices and costs fluctuate around reference values which tend to remain constant for extended periods of time. Prices have an average duration of three weeks. Reference prices have an average duration of about one year, where the reference price of a given item is defined as the most common price of that item during an interval of time. It is possible that variation in reference prices captures most of the variation in prices that matters for macro, that is, most of the variation in prices reflecting the response to macro shocks. Deviations from reference prices tend to be transient, whereas macro shocks tend to be persistent.

2.2 Micro price data in the euro area

The analysis of micro price data in the euro area has been carried out in a project called the Inflation Persistence Network (IPN). The IPN has been a joint undertaking of the European Central Bank and national central banks of the euro area member countries.

[18] Think of waiting to get a haircut on a Saturday, and then getting it at the same published price as on a weekday.

Dhyne at. al. (2005) summarize the findings of the IPN concerning micro data on consumer prices in the euro area.[19] Dhyne at. al. analyze a sample of 50 goods and services common across the euro area member countries. The data are monthly and run from January 1996 to January 2001. The sample of 50 products is representative in the sense that computing the mean frequency of price changes for the same 50 products in the dataset of Bils and Klenow (2004) yields a number close to the mean frequency of price changes in the entire dataset of Bils and Klenow.

Dhyne et al. (2005) find considerable heterogeneity in the frequency of price changes in the euro area, just like in the United States. The frequency of price changes in the euro area ranges from 5.6 percent in "Services" to 28.3 percent in "Unprocessed Food" and 78 percent in "Oil Products". In most sectors the frequency of price changes in the euro area (and its individual member countries) is lower than in the same sector in the United States. This is shown in Table 2.[20]

[Insert Table 2]

Dhyne at. al. (2005) estimate the median price duration of consumer prices in the euro area to be 10.6 months.[21] This estimate is much higher than the U.S. estimate based on posted prices (3.7 months), considerably higher than the U.S. estimate based on regular prices (7.2 months), and somewhat higher than the U.S. estimate based on consecutive regular prices in between forced item substitutions (9.3 months). Forced item substitutions are included in the data analyzed by Dhyne at. al. Unfortunately, different national statistical institutes within the euro area treat sale-related price changes differently. In some countries the reported price excludes the discount even when a sale is known to be in place.[22] Therefore, it is possible that the concept underlying the statement "the median price duration equals 10.6 months in the euro area" is closer to regular prices than to posted prices. Hav-

[19] See also Altissimo, Ehrmann, and Smets (2006) for a survey of the IPN evidence concerning price setting in the euro area.

[20] Table 2 is based on Table 3 from Dhyne at. al. (2005). Note that Dhyne at. al. (2005) find little heterogeneity in the frequency of price changes by country.

[21] Dhyne at. al. (2005) estimate the mean price duration to be 13 months.

[22] Three large countries (Germany, Italy, and Spain) are among the countries in which sale prices are not recorded. In Germany sale prices are recorded only outside an explicit "seasonal sale". See the Technical Appendices 2 and 3 in Dhyne at. al. (2005) regarding forced item substitutions and sales, respectively.

ing said that, it does appear that consumer prices change less frequently in the euro area than in the United States. An interesting research question is what explains this apparent difference in the degree of price rigidity between the two economies.

Dhyne et al. (2005) estimate that the mean size of a price increase in the euro area is 8 percent and the mean size of a price increase in the euro area is 10 percent. The euro-area estimates of the size of price changes are somewhat smaller than the U.S. estimates.[23] At the same time, price changes in the euro area are on average large relative to inflation, just like in the United States.

Vermeulen et al. (2007) provide a comparative analysis of the micro data underlying the producer price indices in Belgium, France, Germany, Italy, Portugal, and Spain. The findings are similar to the findings of Nakamura and Steinsson (2007a) concerning producer prices in the United States. In both economies, there is a great deal of heterogeneity in the frequency of price changes at the wholesale level and producer price changes are large relative to inflation. Vermeulen et al. (2007) investigate what explains the differences in the frequency of price changes across sectors. Table 3 summarizes the findings of Vermeulen et al. (2007) concerning what factors matter for the frequency of price changes.[24] We would like to highlight a few factors. The cost structure matters. Vermeulen et al. (2007) find that firms with a higher labor share in total costs tend to change prices less frequently. Firms with a higher share of intermediate inputs, both energy and non-energy, tend to change prices more frequently. Furthermore, the degree of competition matters. Vermeulen et al. (2007) find that firms operating in more competitive sectors tend to change prices more frequently. The findings of Vermeulen et al. (2007) concerning the impact of energy inputs and the degree of competition accord with the evidence presented by Bils and Klenow (2004) for the United States. Álvarez and Hernando (2007) investigate what explains the differences in the frequency of price changes across sectors using the IPN survey evidence on price setting behavior. Álvarez and Hernando (2007) find that prices tend to be more rigid in countries in which product markets are more regulated, as proxied by an index of product market regulation. More intense product market regulation may be one reason why

[23] Klenow and Kryvtsov (2007) find that the mean absolute size of price changes is 14 percent and 11.3 percent excluding sale-related price changes.

[24] Table 3 reproduces Table 8 from Vermeulen et al. (2007).

prices change less frequently in the euro area than in the United States.

[Insert Table 3]

The IPN provides evidence concerning the degree of synchronization of price changes. Dhyne et al. (2005) compute an index of synchronization due to Fisher and Konieczny (2000). Dhyne et al. (2005) find that the degree of synchronization of price changes is low except for energy prices. The degree of synchronization typically increases as more narrow product categories are considered.

2.3 Cross-country evidence

Bils and Klenow (2004) and the IPN have inspired research on the frequency of price changes in many countries. Álvarez (2007) provides a survey of the recent cross-country evidence based on micro price data. It is useful to think of each study of micro price data as providing a pair of data points, where one data point is the monthly frequency of price changes in a given country in a given period and the other data point is the average monthly rate of inflation in that country in that period. Using the studies listed in Álvarez (2007) and adding a few studies, we end up with a cross section of thirty three observations. Regressing the monthly frequency of price changes on the average monthly rate of inflation yields a statistically significant positive relationship. See Figure 2. Thus the recent cross-country evidence confirms Taylor's (1999) conclusion that the frequency of price changes depends positively on the average rate of inflation.

[Insert Figure 2]

The studies listed in Álvarez (2007) include countries with diverse experiences. According to one study, the frequency of price changes in Sierra Leone was 51 percent between 1999 and 2003 when the average rate of inflation was about 1.5 percent per month. According to another study, the frequency of price changes in Italy was 9.5 percent between 1996 and 2003 when the average rate of inflation was about 0.3 percent per month. Dotsey, King, and Wolman (1999) show that their general equilibrium menu cost model predicts a positive relationship between the frequency of price changes and steady-state inflation. Golosov and Lucas (2007) calibrate a menu cost model to match some features of the BLS data including the frequency of price changes and the average rate of inflation. Golosov and Lucas (2007) show that the menu cost model calibrated to the U.S. data fits well the frequency of price changes and the average rate of inflation during two episodes of high inflation in Israel, documented in Lach and Tsiddon (1992). The model also fits well the evidence from a number of other studies.

Interestingly, the recent cross-country evidence based on micro price data does not support the notion that the average size of price changes depends positively on the average rate of inflation. That there is no support for this notion should not be surprising, given that the average size of price changes is mostly driven by shocks orthogonal to the macro economy and given that the recent cross-country evidence does not include an economy with very high inflation.

2.4 Survey evidence

The IPN has surveyed euro area firms asking about their price setting behavior. Fabiani et al. (2005) analyze the results of the survey.[25] The survey question we would like to focus on is "If there are reasons for changing the price of your main product, which of the following factors may well prevent an immediate price adjustment?". This survey question was followed by a number of possible answers, each answer expressing in simple terms one economic theory. The respondents could indicate their degree of agreement with each economic theory. The responses indicate that firms refrain from changing prices mainly because of explicit and implicit contracts with customers. Physical costs of changing prices (menu costs) are among the reasons for price rigidity least favored by firms, as are costs of information.

This recent euro area evidence from surveys of firms matches well with the same kind of evidence collected earlier in the United States. Blinder et al. (1998) report that when managers of U.S. manufacturing firms were asked why they do not change prices more often than they do, the most common answer was that they feared this would "antagonize" their customers. This response also suggests that firms view recurrent interactions as important. Zbaracki et al. (2004) analyze in detail the pricing behavior of a large manufacturing U.S. company. Zbaracki et al. find that the most important cost of changing prices are "customer

[25] See also Fabiani et al. (2007).

costs", that is, costs of communication and negotiations with customers. Customer costs arise in the presence of long-term relationships. Zbaracki et al. find that customer costs are followed in terms of importance by "managerial costs", that is, costs of information gathering and decision-making. Zbaracki et al. find that the customer costs are more than 20 times, and the managerial costs are more than 6 times the menu costs.

The survey evidence, though it comes with known problems, may well indicate the main reason why prices remain constant for extended periods of time in many sectors of the economy. Firms keep prices unchanged because they worry about repeated interactions with customers. We find it remarkable that the survey evidence matches so well with the classic analysis of "customer markets" by Okun (1981). Okun (1981, p. 141-142) writes: "The firm recognizes its ability to discourage customers from shopping elsewhere by convincing them of the continuity of the firm's policy on pricing, services, and the like. (...) Customers are attracted by continuity because it helps to minimize shopping costs. They know the terms of the previous supplier's offer without shopping if they can count on its continuance; but they must shop to determine the offers of unfamiliar sellers. That information is available, but it can be obtained only at a cost. (...) [C]ustomer markets share the characteristics of career labor markets. Both feature search costs, information costs, and bilateral-monopoly surpluses associated with established relations." Nakamura and Steinsson (2007c) is a recent paper that makes progress modeling the idea of customer markets.

Two more comments concerning the survey evidence are in order. About 75 percent of the firms surveyed by Fabiani et al. (2005) sell their output mainly to other firms.[26] Similarly, Blinder et al. (1998) and Zbaracki et al. (2004) study manufacturing firms operating in wholesale markets. Economists familiar with these studies sometimes express the view that firms operating in retail markets view recurrent interactions as unimportant compared with firms operating in wholesale markets. We think that recurrent interactions matter in some wholesale sectors and some retail sectors. Holding the prior that recurrent interactions matter only for producer prices appears unjustified. At the same time, it may be that considerations other than long-term relationships are the main cause of price rigidity

[26] About two-thirds of the firms in the IPN survey indicate that long-term customers account for the bulk of their sales.

in some sectors of the retail economy.

We also think that the survey evidence does not speak against all models of price setting with imperfect information. In the rational inattention model of Maćkowiak and Wiederholt (2008) an individual firm is very well informed about its environment. The firm's private marginal value of information is low. Therefore it is to be expected that in a survey the firm responds that it is very well informed. Furthermore, in a survey a firm is asked why it sometimes fails to change the price of its product. Models of price setting with imperfect information typically seek to explain why the price responds slowly to macro shocks, conditional on the price being changed.[27]

Let us conclude Section 2 with a summary. The new micro price data from the United States and the euro area share a number of characteristics. Both in the U.S. and in the euro area there is a lot of heterogeneity in the frequency of price changes, prices remain constant for extended periods of time in many sectors of the economy, prices change on average by large amounts relative to inflation, and the survey evidence indicates that firms perceive long-term relationships as the main reason why prices remain constant for some time. Consumer prices appear to change less frequently in the euro area than in the United States. The median consumer price lasts about 4 months in the U.S. economy, about 7 months when price changes related to sales are excluded, and about 9 months when price changes related to both sales and forced item substitutions are excluded. The median consumer price lasts about 11 months in the euro area economy. The frequency of price changes depends positively on the average rate of inflation in a cross-section of countries.

3 Rejecting the null

In this section we discuss the recent literature that compares standard models of price setting used in macroeconomics to the new micro data. Clearly, the new micro data support the basic premise underlying the New Keynesian or New Neoclassical Synthesis perspective: prices of many goods and services remain constant for extended periods of time. At the same time though, standard models of price setting used in macroeconomics are so simple

[27] A more complete model would need to explain both the response of prices to different kinds of shocks and why prices remain fixed for some time.

that each of the models is bound to be "rejected". Each of the models is at odds with some aspect of the detailed micro data that we now have.[28]

Klenow and Kryvtsov (2007) and Nakamura and Steinsson (2007a) document a number of features of the BLS micro price data in addition to the frequency and the size of price changes. Both papers compare the main features of the micro data to standard models of price setting used in macroeconomics. Klenow and Kryvtsov (2007) emphasize the following features of the BLS micro price data in addition to the frequency and the size of price changes. Price durations for a given product are variable. Hazard rates for a given product are approximately flat. The size of price changes for a given product is unrelated to the time since the previous change. The intensive margin dominates the variance of inflation.[29] Nakamura and Steinsson (2007a) reach somewhat different conclusions concerning some features of the BLS micro price data, which signals that what "stylized facts" one reports depends to some degree on one's dataset and methodology. Furthermore, Nakamura and Steinsson stress some features of the data that do not receive emphasis from Klenow and Kryvtsov. One feature of the data noted by Nakamura and Steinsson that seems important is seasonality. The frequency of price changes is highly seasonal. It is highest in the first quarter and lowest in the fourth quarter.

Klenow and Kryvtsov (2007) report that the menu cost model of Golosov and Lucas (2007) fails to generate enough small price changes. The reason is that the model has a single, fairly large menu cost. The model needs a fairly large menu cost in order to match the large average absolute size of price changes. Furthermore, only if the elasticity of substitution between products is set to a number like two can the Golosov-Lucas model yield flat hazard rates and approximately no relationship between the size of price changes and the time since the previous price change. Interestingly, in the Golosov-Lucas model the intensive margin drives inflation movements. The fraction of price changes is stable because

[28] See Álvarez (2007) and Gaspar, Levin, Martins, and Smets (2007) for surveys of how the new micro data compare to standard models of price setting used in macroeconomics.

[29] Inflation is the product of the fraction of products with price changes (the extensive margin) and the average size of those price changes (the intensive margin). Klenow and Kryvtsov (2007) estimate that the intensive margin accounts for 94 percent of inflation's variance for posted prices and 91 percent for regular prices.

prices are changed mostly in response to large idiosyncratic shocks rather than small macro shocks. Since the Golosov-Lucas model also produces small real effects of nominal shocks, we now know that real effects can be small even if the extensive margin is unimportant.

Klenow and Kryvtsov (2007) study a version of the Calvo model with idiosyncratic shocks. They find that the model predicts larger absolute size of price changes for older prices, in contradiction to the micro data. Klenow and Kryvtsov also study a Taylor model with multiple sectors. The Taylor model fails to produce variable price durations and flat hazard rates. We would like to add that it is an open question whether a menu cost model or a Calvo model can give a plausible account of the seasonality in the micro data.

A number of recent papers analyze scanner data and compare the data to standard models of price setting used in macroeconomics. Eichenbaum, Jaimovich and Rebelo (2008) study a new weekly scanner dataset from a major U.S. retailer that contains information on prices, quantities, and costs for over 1000 stores. Eichenbaum, Jaimovich and Rebelo find that prices are more volatile than marginal costs. Furthermore, the probability of a price change increases in the deviation of the markup from its mean. Prices typically adjust when the markup deviates by more than 20 percent from its mean. Eichenbaum, Jaimovich and Rebelo argue that neither a standard Calvo model nor a standard menu cost model can match the data. The Calvo model is inconsistent with the observed state dependence of prices. The menu cost model predicts that prices should be less volatile than marginal costs. Campbell and Eden (2007) analyze a different scanner dataset. Campbell and Eden also find state dependence of prices. The probability of a price change is highest when a store's price differs substantially from the average of other stores' prices.

Macroeconomists recently gained access to new, detailed micro price data. They confront the micro data with familiar and tractable models of price setting. The models are such crude approximations to the real world and the micro data are so detailed that, not surprisingly, the models fail. The micro data are not only rich, in the sense that a lot goes on for a given product category, but also reveal a lot of heterogeneity across products. There is heterogeneity in terms of the frequency and size of price changes, but also in terms of how frequent sales are, what form sales take, and how frequent forced item substitutions are. The wholesale economy seems to differ from the retail economy. The heterogeneity in the micro data makes us skeptical that economists should aim at developing "the model" of price rigidity. Different models of price rigidity may be necessary for different sectors of the wholesale and retail economy. Furthermore, it is an open question whether models of price rigidity that fit micro data well will imply the kinds of impulse responses to macro shocks that we see in macro data.

4 Mapping micro price data into macro models

One reason why macro modelers are interested in micro price data is that in familiar and tractable macro models the frequency of price changes maps easily into impulse responses of prices and quantities to shocks. In the Calvo model a lower frequency of price changes implies larger and more persistent real effects of nominal shocks, other things being equal. The same is typically true in a menu cost model. In this section we argue that there is no simple mapping from the frequency of price changes in micro data to impulse responses of prices and quantities to shocks.

This point is not new. We know there exist models with physically rigid prices in which nominal shocks have no real effects, and we know there exist models with perfectly flexible prices in which nominal shocks can have large and persistent real effects. In the menu cost model of Caplin and Spulber (1987) nominal shocks have no real effects despite the fact that individual prices are adjusted infrequently. Sims (1998) provides a more recent, perhaps less familiar example that we discuss at some length. Sims (1998) considers a model with nominal wage contracts that do not represent open-ended commitments to provide labor at a given wage rate. This is in contrast to most models of nominal rigidity which assume that workers supply as much labor as firms demand at a given wage rate and firms produce as much output as consumers demand at a given price. In Sims's model individual workers are working or not. If their contract specifies a nominal wage that turns out to be low in real terms, they lose at the expense of firms. But since workers own firms, an "expansionary" nominal shock in Sims's model only "redistributes" wealth from workers to firms and back to workers. Output is unaffected.

At the opposite end of the spectrum of models, Woodford (2002), Mankiw and Reis

(2002), Reis (2006), and Maćkowiak and Wiederholt (2008) develop the idea of Phelps (1970) and Lucas (1972) that real effects of nominal shocks are due to imperfect information. In these recent models nominal shocks can have large and persistent real effects, despite the fact that individual prices are adjusted frequently. In the rest of this section we would like to use the research of each of us to illustrate anew, in two different ways, the point that mapping micro price data into macro models is complicated.

4.1 Impulse responses of sectoral price indices

Maćkowiak, Moench and Wiederholt (2008) estimate impulse responses of sectoral price indices to common shocks and sector-specific shocks. If the frequency of price changes were decisive for impulse responses of prices to shocks, one would expect sectoral price indices to respond with roughly equal speed to both kinds of shocks. Maćkowiak, Moench and Wiederholt estimate a Bayesian unobservable index model using monthly sectoral consumer price indices from the U.S. economy for the period 1985 until 2005. The unobservable index model is motivated by the optimal pricing equation arising in the rational inattention model of Maćkowiak and Wiederholt (2008). The optimal pricing equation is

$$p_{nt} = \alpha_n (L) f_t + \beta_n (L) v_{nt}, \tag{1}$$

where p_{nt} is the price index in period t in sector n, $n = 1, ..., N$, $\alpha_n (L)$ and $\beta_n (L)$ are polynomials in the lag operator L, the variable f_t follows a Gaussian white noise process with unit variance, and each variable v_{nt} follows a Gaussian white noise process with unit variance. The processes v_{nt} are pairwise independent and independent of the process f_t. In this optimal pricing equation $\alpha_n (L)$ is the impulse response of the price index in sector n to an aggregate shock and $\beta_n (L)$ is the impulse response of the price index in sector n to a sector-specific shock.[30] Differencing equation (1) yields

$$\pi_{nt} = A_n (L) f_t + B_n (L) v_{nt}, \tag{2}$$

where $\pi_{nt} = (1 - L) p_{nt}$, $A_n (L) = (1 - L) \alpha_n (L)$, and $B_n (L) = (1 - L) \beta_n (L)$. Maćkowiak, Moench and Wiederholt (2008) estimate the equation (2) for $n = 1, ..., N$ in order to infer the

[30] It is straightforward to generalize the model such that the variable f_t follows a vector Gaussian white noise process with covariance matrix identity.

impulse responses of sectoral price indices to common shocks and sector-specific shocks.[31]

Maćkowiak, Moench and Wiederholt (2008) find that most of the variation in sectoral price indices, about 85 percent, is caused by sector-specific shocks. Sectoral price indices are very volatile relative to the aggregate price level. Figure 3 shows the cross section of the impulse responses of sectoral price indices to sector-specific shocks. Note that this is a posterior distribution taking into account both parameter uncertainty and variation across sectors.[32] It is apparent that sectoral price indices respond quickly to sector-specific shocks. Essentially 100 percent of the long-run response occurs within one month. In this sense sectoral price indices are not sticky at all. Figure 3 is reminiscent of the one-to-one impulse response of the aggregate price level to money in the Caplin-Spulber model.

Figure 4 shows the cross section of the impulse responses of sectoral price indices to an aggregate shock. Sectoral price indices respond slowly to aggregate shocks. About 15 percent of the long-run response occurs within one month. In this sense sectoral price indices are sticky. These findings accord with the idea that the degree of stickiness of prices – defined as the speed of response of prices to disturbances – is conditional on the source of the disturbance. Prices in the same sector, which get assigned the same frequency of changes in micro studies, respond quickly to sector-specific shocks and slowly to macro shocks.

[Insert Figures 3-4]

The findings of Maćkowiak, Moench and Wiederholt (2008) are complementary to the findings of Boivin, Giannoni, and Mihov (2007) who use different sectoral data from the United States, a different model, and different estimation methodology to address a similar set of questions. Boivin, Giannoni, and Mihov (2007) also find that sectoral price indices respond quickly to sector-specific shocks and slowly to aggregate shocks.[33] Having said that,

[31] The equation (2) for $n = 1, ..., N$ has the same form as the unobservable index model of the business cycle proposed by Sargent and Sims (1977).

[32] To derive this figure and the subsequent figure sectoral inflation rates have been normalized to have variance unity. This normalization makes impulse responses comparable across sectors. Figures 3 and 4 are reproduced from Maćkowiak, Moench and Wiederholt (2008).

[33] Furthermore, Boivin, Giannoni, and Mihov (2007) estimate impulse responses of sectoral price indices to monetary policy shocks. Boivin, Giannoni, and Mihov find that sectoral price indices respond slowly to monetary policy shocks, just like the aggregate price level.

there is evidence that the frequency of price changes helps explain the speed of impulse responses of prices to macro shocks in a cross-section of sectors. The results of Boivin, Giannoni, and Mihov (2007) and Maćkowiak, Moench and Wiederholt (2008) are consistent with the idea that sectors in which prices are adjusted more frequently tend to respond faster to macro shocks. In the data there is a strong positive relationship between the frequency of price changes and the size of sector-specific shocks.[34] Therefore it is reasonable to conclude that prices in sectors facing greater sector-specific uncertainty tend to respond faster to macro shocks. This is consistent with the menu cost model and the imperfect information model of Reis (2006). This is also consistent with the rational inattention model of Maćkowiak and Wiederholt (2008) if all firms are assumed to have the same marginal value of information and if profit functions of firms in more volatile sectors tend to be more sensitive to errors in price setting.

In a recent paper McCallum and Smets (2008) estimate the effects of monetary policy shocks in the euro area using a large dataset of area-wide, country-specific and sector-specific time series for the period 1987 to 2005. McCallum and Smets (2008) employ the factor-augmented VAR methodology proposed by Bernanke, Boivin, and Eliasz (2005) and used by Boivin, Giannoni, and Mihov (2007). We added five sectoral consumer price indices from the three largest euro area countries (Germany, France, and Italy) to the dataset of McCallum and Smets (2008). The five sectors are unprocessed food, processed food, non-energy industrial goods, energy, and services.[35] We computed the impulse responses of the sectoral price indices to a monetary policy shock. The impulse responses are plotted in Figure 5 together with the impulse response of the euro-area harmonized index of consumer prices to the same shock. The sectoral price indices fall slowly after a contractionary monetary policy shock, as does the aggregate price level. We assigned to each sectoral price index a frequency of price changes, based on the results of the IPN. Figure 6 shows a statistically significant, negative relationship between the response to a monetary policy shock after 8 quarters in a given sector and the frequency of price changes in that sector.

[34] A positive relationship between the frequency of price changes and the size of sector-specific shocks is consistent with the menu cost model.

[35] The data on sectoral consumer price indices were kindly provided by Benoît Mojon. See Altissimo, Mojon, and Zaffaroni (2007).

Sectors in which prices change frequently tend to respond more strongly to a monetary policy shock. The findings based on the model of McCallum and Smets (2008) confirm that the frequency of price changes helps explain the speed of impulse responses of prices to macro shocks in a cross-section of sectors.

[Insert Figures 5-6]

4.2 DSGE models

The second example involves the DSGE model of Smets and Wouters (2003). The Smets-Wouters model has a marginal likelihood that is comparable to that of an unconstrained, low-order VAR. The price setting and the wage setting mechanisms in the model are a mixture of the Calvo mechanism and a backward-looking component (indexation). Sahuc and Smets (2008) estimate a variant of the Smets-Wouters model using quarterly aggregate data from 1985 to 2004 for, alternatively, the United States and the euro area. The slope of the New Keynesian Phillips Curve is estimated to be very low and somewhat lower in the euro area than in the U.S. (0.008 versus 0.012). Since the slope of the New Keynesian Phillips Curve is inversely related to the Calvo parameter capturing the frequency of price changes, the Smets-Wouters model reflects the notion that prices change less frequently in the euro area compared to the United States, as is apparent from micro data. However, the model does so only weakly: the difference is not statistically significant and not large economically.[36] Furthermore, without real rigidity of some form the estimated value of the Calvo parameter is very high (0.91 in the euro area and 0.89 in the United States). Whether prices change on average every 4 months or every 11 months, nominal rigidity by itself does not suffice to explain the low slope of the New Keynesian Phillips Curve. One needs to combine nominal stickiness with a sufficient degree of real rigidity. Smets and Wouters (2007) replace the Dixit-Stiglitz aggregator with the Kimball aggregator in estimation using U.S. data.[37] This increases the degree of real rigidity in the model, as the price elasticity of demand becomes increasing in the firm's price. Therefore prices in the

[36] Galí and Gertler (1999) and Galí, Gertler, and López-Salido (2001) estimate the New Keynesian Phillips Curve using GMM for the United States and the euro area. Their findings are consistent with the notion that prices change less frequently in the euro area compared to the United States.

[37] See Kimball (1995).

model respond by smaller amounts to shocks, for a given frequency of price changes. Smets and Wouters obtain a much smaller estimate of the Calvo parameter, about 2/3. A value for the Calvo parameter of about 2/3 implies that price contracts last 3 quarters on average. The Kimball aggregator plus the Calvo parameter equal to about 2/3 yield roughly the same fit to U.S. macro data as the Dixit-Stiglitz aggregator plus the Calvo parameter equal to about 0.9. That the frequency of price changes in micro data does not map easily to impulse responses in the Smets-Wouters model should not come as a surprise. The Smets-Wouters model is intended to capture the impulse responses of the aggregate price level and other macro variables to macro shocks. The price setting mechanism embedded in the Smets-Wouters model is a stand-in for "how prices respond to macro shocks" not for "how prices are being set at the micro level".

Note also that in the Smets-Wouters model all prices change every quarter because of indexation.[38] This creates a difficulty mapping the Calvo parameter in the model to the micro price data. It is possible that the model with the "rule-of-thumb" behavior as in Galí and Gertler (1999) instead of indexation would fit the macro data equally well. In the Galí-Gertler model some firms keep prices unchanged each period. The importance of backward-looking model elements in matching the macro data accords well with the idea that some form of imperfect information about macro shocks matters for macro dynamics. More generally, the fact that prices change does not imply that prices reflect perfectly all available information.

The likelihood of a DSGE model like the Smets-Wouters model peaks in a region of the parameter space implying that prices and quantities move slowly in response to most macro shocks. The model is capable of matching this pattern in macro data via a combination of some Calvo rigidity and sufficient real rigidity of some form. Presumably, one could replace the Calvo rigidity with some other form of nominal stickiness, say based on imperfect information. The point is that the model needs both nominal stickiness of some form and sufficient real rigidity of some form. How frequently prices change is not decisive. What is decisive is how price setting interacts with other features of the economy to produce sluggish impulse responses to macro shocks.[39] We discuss modeling different kinds of real rigidity

[38] See also Christiano, Eichenbaum, and Evans (2005).

[39] Sahuc and Smets (2008) compare impulse responses to a monetary policy shock in a model with a higher

in Section 5.2.

5 The road ahead

In an ideal world macroeconomists would set up, solve and understand a DSGE model with many heterogeneous firms and households, in which firms and customers in different sectors interact differently, and which matches in detail both micro data and macro data. Realistically all we can hope for, at least for some time, is a model that matches macro data in detail while telling a reasonable story broadly in line with micro data. The recent DSGE models have made progress matching macro data in detail. In this section we survey the recent literature on models of price setting. We search for a story or a set of stories that would simultaneously: (i) imply persistent impulse responses to macro shocks, similar to the impulse responses in the Smets-Wouters model; (ii) be broadly in line with micro price data.

5.1 Making a state dependent model behave like an exogenous timing model

After Bils and Klenow (2004) and others had begun analyzing the BLS data, Golosov and Lucas (2007) constructed a menu cost model and calibrated the model to match some features of the BLS data. Golosov and Lucas found that the model needed large firm-specific productivity shocks in order to match the large average absolute size of price changes in the data. Furthermore, Golosov and Lucas found that their calibrated model predicted small real effects of nominal shocks.

There are two reasons why real effects of nominal shocks are small in the calibrated Golosov-Lucas model. Price adjustment in the model is triggered almost always by idiosyncratic shocks, because idiosyncratic shocks in the model are much larger than aggregate shocks. But in the menu cost model the identity of shocks does not matter. The size of shocks matters. Once a firm decides to adjust its price, the firm makes the price respond

Calvo parameter like in the euro area with those in a model with a lower Calvo parameter like in the United States, keeping the other frictions constant. They find that the differences are minimal.

to all shocks independent of which shock has triggered the price adjustment. Since idiosyncratic shocks trigger price adjustments fairly frequently, prices respond to nominal shocks fairly quickly.

Furthermore, in a state dependent model there is a selection effect. In the absence of macro shocks some firms increase prices and some firms decrease prices in response to idiosyncratic shocks of sufficient magnitude. Suppose that an expansionary nominal shock arrives. Some firms that were going to decrease prices by a lot in the absence of the macro shock now keep prices constant. In an exogenous timing model there are no such firms. Also, some firms that barely decided not to increase prices in the absence of the macro shock now increase prices by a sizable amount. In an exogenous timing model there are no such firms, either. Due to the selection effect the price level increases by more in a state dependent model than in an exogenous timing model. The selection effects can be quantitatively important. The analysis of Caballero and Engel (2007) suggests that the degree of flexibility of the price level in state dependent model is about three times larger compared with an exogenous timing model with the same average frequency of price changes.

Midrigan (2006) shows how one can dampen the selection effect.[40] Midrigan notes in scanner data that prices of goods sold by a particular retailer, especially those in narrow product categories, tend to adjust simultaneously. He uses this observation to motivate a model in which a two-product firm faces a fixed cost of changing one of its prices, but, conditional on paying this cost, zero marginal cost of resetting the other price. The firm's profit function is affected by nominal shocks and idiosyncratic shocks drawn from a density with fat tails. Midrigan's model can match simultaneously the observation that the average absolute size of price changes is large and the observation that many price changes are small. This is in contrast to the Golosov-Lucas model. Also in contrast to the Golosov-Lucas model, Midrigan's model predicts real effects of nominal shocks roughly similar in size to an exogenous timing model. Compared to the Golosov-Lucas model, fewer firms that were going to decrease prices in the absence of an expansionary nominal shock keep prices constant when the shock occurs. Similarly, fewer firms that were going to keep prices unchanged in the absence of an expansionary nominal shock increase prices when the shock

[40] See also Gertler and Leahy (2006).

occurs. The reason is that the density of price changes is leptokurtic. There is a small mass of firms near the points where the decision to change prices or not is made.

There are reasons to think that generalizing the menu cost model to include imperfect information makes the model behave somewhat closer to an exogenous timing model. We discuss this idea in Section 5.3.

5.2 Modeling the kind of real rigidity that works

Modelers who introduce real rigidity into a DSGE model usually do so at the level of individual firms or sectors. Examples of the former, more common approach are the Kimball aggregator and firm-specific inputs. With the Kimball aggregator the price elasticity of demand faced by a firm is increasing in the firm's price. With firm-specific inputs a firm's marginal cost function is increasing in the firm's output.[41] An example of the latter approach are local (sectoral) labor markets as in the state-dependent model of Gertler and Leahy (2006). We think that at present neither approach implies that the DSGE model provides a completely satisfactory story about price setting behavior. Real rigidity means that when firms change prices they change prices by small amounts.[42] When real rigidity enters at the level of individual firms, firms change prices by small amounts in response to *all* shocks. When real rigidity enters at the level of individual sectors, firms change prices by small amounts in response to sectoral and aggregate shocks. Both kinds of real rigidity are not easy to reconcile with micro data. In micro data price changes are large relative to inflation. Furthermore, sectoral price indices respond quickly to sector-specific shocks. Conditional on having changed prices, firms do not seem to be worried about moving prices a lot in response to firm-specific and sectoral shocks. There appears to be little evidence for significant real rigidity at the level of individual firms and sectors. Burnstein and Hellwig (2007), Dotsey and King (2005), and Klenow and Willis (2006) investigate the effects of

[41] Eichenbaum and Fisher (2007) estimate different variants of the Calvo model finding that introducing the Kimball aggregator and firm-specific capital increases the estimated frequency of price adjustment.

[42] Altig, Christiano, Eichenbaum, and Linde (2005) show that introducing firm-specific capital into a DSGE model with the Calvo mechanism increases the estimated frequency of price adjustment. However, introducing firm-specific capital also decreases the size of price changes. Altig, Christiano, Eichenbaum, and Linde estimate an elasticity of prices to real marginal costs of 0.04.

firm-level real rigidity in menu cost models. These authors find that the menu cost model with significant firm-level real rigidity needs a combination of very large idiosyncratic shocks and very large menu costs in order to match the large size of price changes in the data.

The kinds of real rigidity that seem promising are ones that arise conditionally on macro shocks. What we have in mind are features of the economy such that firms find it optimal to change prices by large amounts in response to idiosyncratic shocks and, at the same time, firms find it optimal to change prices by small amounts in response to aggregate shocks. Nakamura and Steinsson (2007b) develop a multi-sector menu cost model introducing real rigidity via intermediate inputs, as in Basu (1995). The degree of monetary non-neutrality generated by the model with intermediate inputs is roughly triple that of the model without intermediate inputs. Firms that change prices soon after a nominal shock adjust less than they otherwise would because the prices of many of their inputs have not yet responded to the shock. At the same time, introducing real rigidity via intermediate inputs does not dampen the size of price changes in response to idiosyncratic shocks. Nakamura and Steinsson (2007b) also find that their multi-sector menu cost model generates much larger real effects of nominal shocks than a single-sector menu cost calibrated to the mean frequency of price changes of all firms. The interaction between heterogeneity and aggregate-level real rigidity seems worth exploring further in future research. Furthermore, recall from Section 2 that the IPN evidence on determinants of the frequency of price changes points to the labor share as one determinant of the frequency of price changes. Slow responsiveness of wages may be another source of aggregate-level real rigidity that interacts with price setting behavior. Kryvtsov and Midrigan (2008) is a recent paper assessing the degree of real rigidity, where real rigidity may take the form of sluggish wages.

5.3 Rational inattention and sticky information

The idea that real effects of nominal shocks are due to imperfect information does not rely on physical rigidity of prices. Instead, prices are postulated not to respond perfectly to shocks. Lucas (1972) formalized this idea by assuming that agents observe the current state of monetary policy with a delay. The Lucas model has been criticized on the grounds that information concerning monetary policy is published with little delay. However, Sims (2003) points out that if agents cannot map perfectly all available information into decisions, there is a difference between publicly available information and the information actually reflected in agents' decisions.

Maćkowiak and Wiederholt (2008) develop a model in which information concerning the current state of monetary policy is publicly available but it is optimal for agents to pay little attention to this information. In the model price setting firms decide what to pay attention to. Firms' inability to process all available information is modeled as a constraint on information flow, as in Sims (2003). Firms face a trade-off between paying attention to aggregate conditions and paying attention to idiosyncratic conditions. Impulse responses of prices to shocks are sticky – dampened and delayed relative to the impulse responses under perfect information. The extent of stickiness in a particular impulse response depends on the amount of attention allocated to that type of shock. When idiosyncratic conditions are more variable or more important than aggregate conditions, firms pay more attention to idiosyncratic conditions than to aggregate conditions. Prices then respond strongly and quickly to idiosyncratic shocks, and at the same time prices respond weakly and slowly to aggregate shocks. In addition, there are feedback effects because firms track endogenous aggregate variables (the price level and real aggregate demand). When firms pay limited attention to aggregate conditions, the price level reacts less to a nominal shock than under perfect information. If prices are strategic complements, this implies that firms find it optimal to pay even less attention to aggregate conditions; the price level reacts even less and so on.

Maćkowiak and Wiederholt (2008) calibrate their model and find, like Golosov and Lucas (2007) and others working with menu cost models, that to match the large average absolute size of price changes in the micro data idiosyncratic volatility in the model has to be one order of magnitude larger than aggregate volatility. This implies that firms allocate almost all attention to idiosyncratic conditions. Therefore, prices respond strongly and quickly to idiosyncratic shocks, but prices respond only weakly and slowly to nominal shocks. Nominal shocks have strong and persistent real effects. The key feature of the model is that identity of shocks matters.

Mankiw and Reis (2002) develop a different model in which information disseminates slowly. Mankiw and Reis assume that every period a fraction of firms obtains perfect information concerning all current and past disturbances, while all other firms continue to set prices based on old information. Reis (2006) shows that a model with a fixed cost of obtaining perfect information can rationalize this kind of slow information diffusion. Note that in Mankiw and Reis (2002) and Reis (2006) prices respond with equal speed to all disturbances.

Woodford (2008) relaxes the assumption that a firm in a menu cost model is perfectly aware of its economic environment in between price changes. Woodford models the firm in between price changes as being subject to an information constraint, as in Sims (2003). As the firm's marginal value of information increases, Woodford's model behaves progressively more like an exogenous timing model and less like a state dependent model. In particular, in Woodford's model the firm occasionally pays the menu cost "by mistake" and ends up changing the price by a small amount. Moscarini (2004) studies optimal sampling frequency in a quadratic tracking problem with an information constraint. Moscarini shows that as the economic environment becomes less predictable the optimal sampling frequency may rise or fall. Benefits of more frequent sampling increase, as in a model with perfect information, but costs of more frequent sampling increase as well under rational inattention.

5.4 Modeling rigid prices without a menu cost

Models in which prices remain constant for some time because there is a fixed cost of changing them are useful exploratory devices. The same can be said about models in which firms face different fixed costs for changing prices of different products, firms face different fixed costs for changing regular prices and sale prices, or firms face fixed costs that vary randomly with the variation being orthogonal to the firms' economic environment. Ultimately one would like to know why costs of changing prices arise and how such costs depend on firms' economic environment. The idea of customer markets seems promising in this regard. Nakamura and Steinsson (2007c) model the idea of customer markets. Nakamura and Steinsson observe that if consumers form habits in individual goods, firms face a time-inconsistency problem. Consumers' habits imply that demand is forward-looking. Low prices in the future help attract consumers at present. Therefore firms want to promise low prices in the future.

But when the future arrives firms have an incentive to exploit consumers' habits and raise prices. Nakamura and Steinsson show that implicit contracts involving price rigidity can be sustained as equilibria in the infinitely repeated game played by a firm and its customers.

Rational inattention may also provide an explanation for why prices remain constant for some time. Maćkowiak and Wiederholt (2008) analyze their model of price setting after taking a log-quadratic approximation to the firms' objective function. After a log-quadratic approximation to the firms' objective function the distribution of the price response to shocks is Gaussian. This implies that prices respond smoothly to all shock realizations. In Maćkowiak and Wiederholt (2007) the authors solve a rational inattention problem of an individual firm without taking a log-quadratic approximation to the firm's objective function. The distribution of the price response to shocks is close to a Gaussian distribution when the firm's marginal value of information is low. When the firm's marginal value of information is high the distribution of the price response to shocks has only a few mass points. This implies that the price fails to respond to some shock realizations. In the future, modeling the interaction of firms and consumers, with rational inattention on both sides of the market, may provide an explanation for rigidity of prices without implying that marginal value of information on either side of the market is high.[43]

6 Concluding remarks

It is possible that several models will emerge consistent with the impulse responses we see in macro data. Each model may have different implications for some feature of micro data. Therefore using micro data may be helpful for discriminating between the models. Furthermore, each model may have different implications for welfare consequences of macro fluctuations. For example, in a rational inattention model welfare costs of day-to-day macro fluctuations tend to be modest, at least so long as the marginal value of information is small from the viewpoint of agents in the model. Welfare costs of day-to-day macro fluctuations are much larger in the Calvo model. The reason is that on average agents in the Calvo model

[43] In a different strand of the literature, Rotemberg (2004) develops a model in which firms wishing to avoid customers' anger keep price rigid under some circumstances when prices would change under standard assumptions.

are further away from their first-best unconstrained decisions compared to agents in the rational inattention model. In sticky information models welfare costs of day-to-day macro fluctuations tend to be large, because at any time some agents are quite poorly informed about their economic environment. On the other hand, in rational inattention models an increase in macro volatility can be very costly, because tracking the aggregate economy becomes increasingly difficult as the macroeconomic environment gets less predictable.

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Figure 1: Frequency of Price Changes by Entry Level Item for 1998-2005, from Nakamura and Steinsson (2007a)

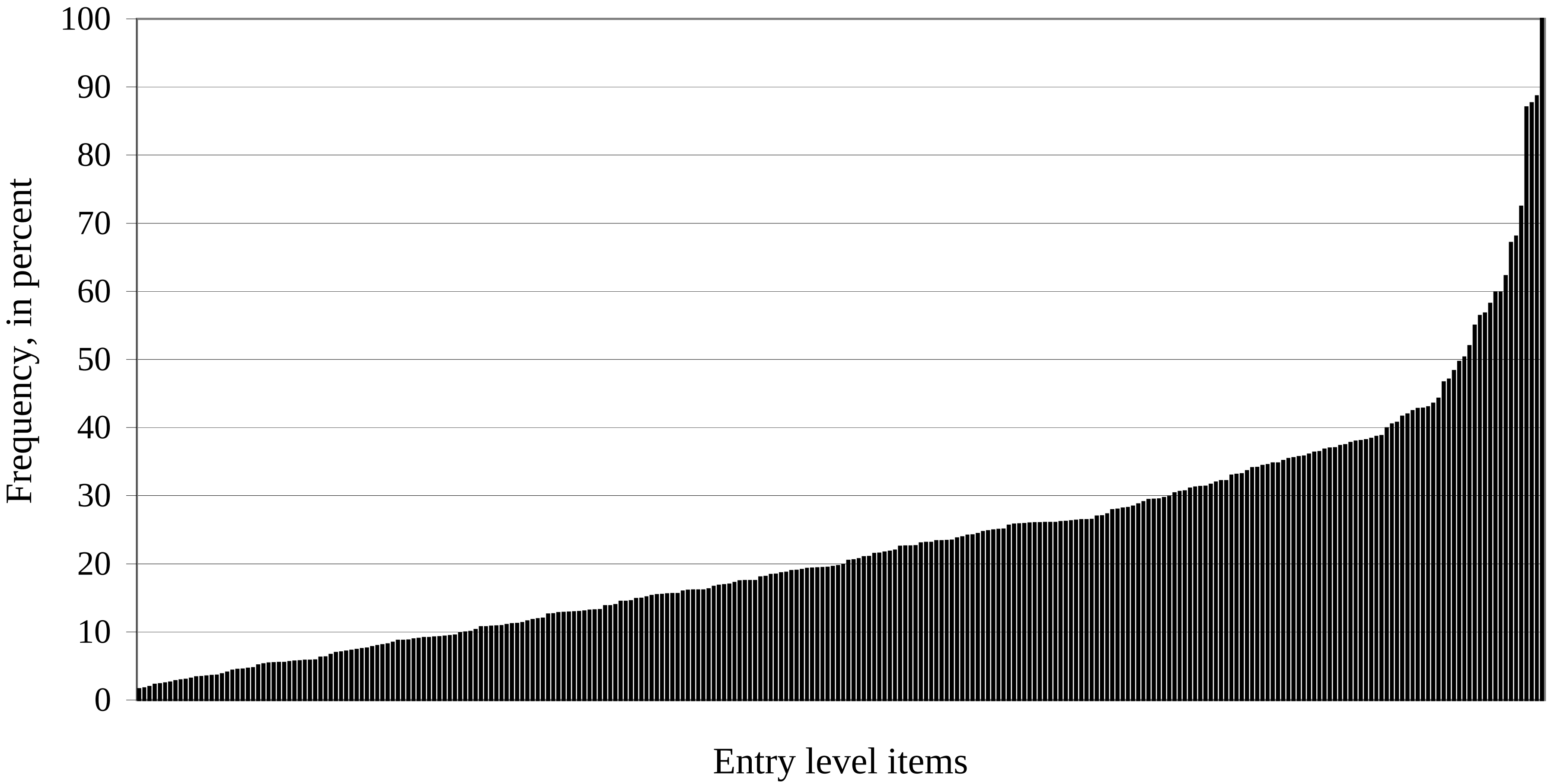


Table 1: Frequency of Price Changes by Major Group for 1998-2005, from Nakamura and Steinsson (2007a)

Major Group	Median frequency of price changes, in percent
Services excluding Travel	6.6
Recreation Goods	11.9
Other Goods	15.5
Household Furnishings	19.4
Processed Food	25.9
Apparel	31.0
Transportation Goods	31.3
Unprocessed Food	37.3
Utilities	38.1
Travel	42.8
Vehicle Fuel	87.6

Table 2: Average Frequency of Price Changes by Product Type, Euro Area vs. the U.S., from Dhyne et al. (2005)

	Unprocessed Food	Processed Food	Energy (Oil Products)	Non-Energy Industrial Goods	Services
Austria	37.5	15.5	72.3	8.4	7.1
Belgium	31.5	9.1	81.6	5.9	3.0
Germany	25.2	8.9	91.4	5.4	4.3
Spain	50.9	17.7	n.a.	6.1	4.6
Finland	52.7	12.8	89.3	18.1	11.6
France	24.7	20.3	76.9	18.0	7.4
Italy	19.3	9.4	61.6	5.8	4.6
Luxembourg	54.6	10.5	73.9	14.5	4.8
Netherlands	30.8	17.3	72.6	14.2	7.9
Portugal	55.3	24.5	15.9	14.3	13.6
Euro Area	28.3	13.7	78.0	9.2	5.6
U.S.	47.7	27.1	74.1	22.4	15.0

Note: The estimates for the U.S. are based on Bils and Klenow (2004).

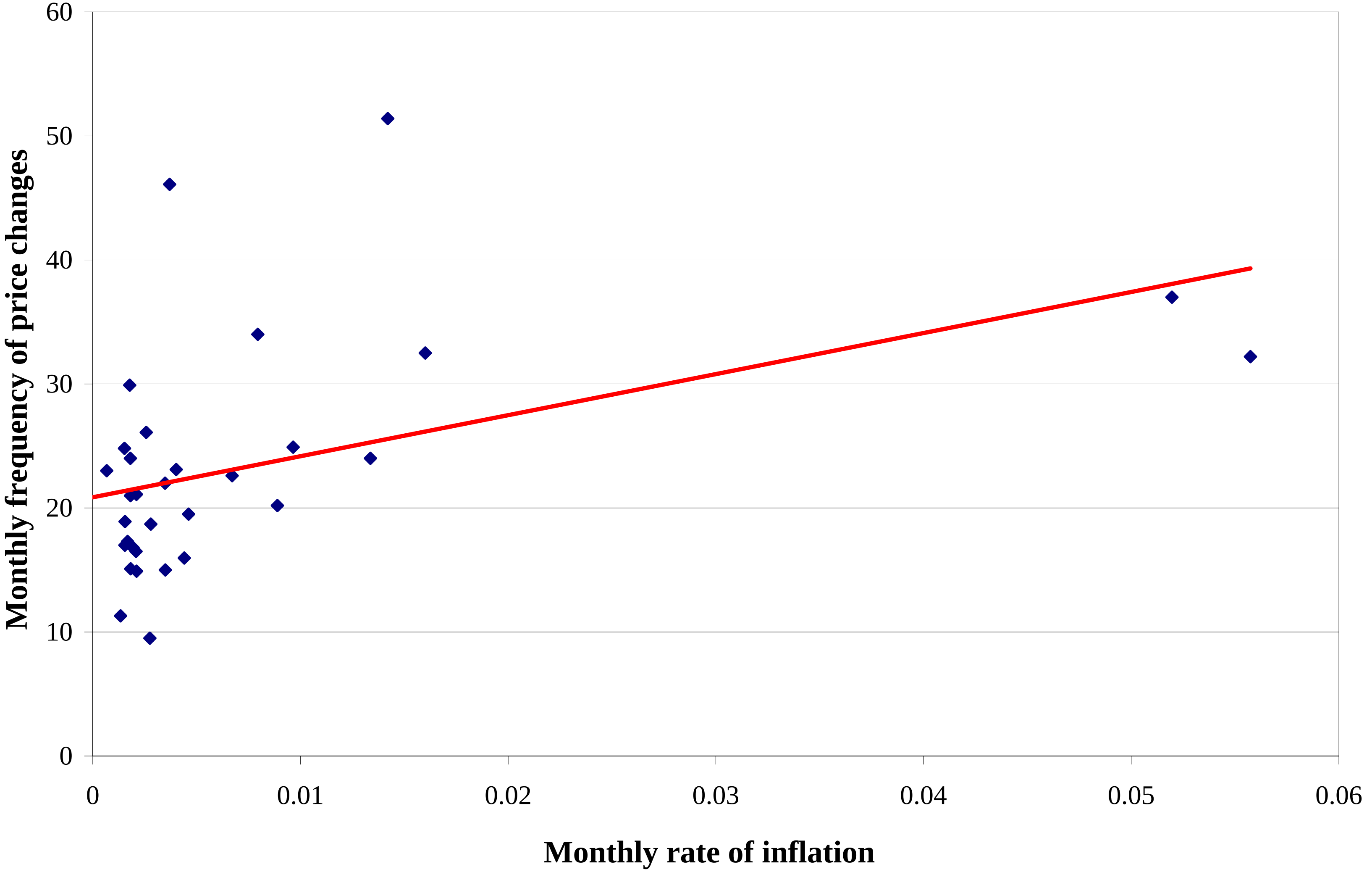
Table 3: Factors Affecting the Frequency of Producer Price Changes, from Vermeulen et al. (2007)

	Belgium	France	Germany	Italy	Portugal	Spain
Share of labour in costs	Yes	Yes	Yes	Yes	n.a.	Yes
Share of intermediate inputs in costs						
- energy	Yes	n.a.	Yes	Yes	Yes	Yes
- non energy	Yes	n.a.	Yes	Yes	Yes	Yes
Inflation	n.a.	Yes	Yes	n.a.	n.a.	Yes
Competition	Yes	Yes	n.a.	n.a.	n.a.	Yes
Seasonality	Yes	Yes	Yes	Yes	Yes	Yes
Attractive prices	n.a.	n.a.	Yes	Yes	n.a.	Yes
Regulated prices	n.a.	n.a.	n.a.	n.a.	n.a.	Yes
Changes in VAT rates	n.a.	Yes	Yes	n.a.	n.a.	Yes

"Yes" denotes that the factor has an impact on the frequency of price changes;

"n.a" indicates that the impact of the factor on the frequency of price changes has not been analyzed.

Figure 2: Frequency of Price Changes vs. Inflation in a Cross Section of Countries



Impulse Responses of Sectoral Price Indices, with 68% and 90% Bands, from Maćkowiak, Moench, and Wiederholt (2008)

Figure 3: Impulse Responses to Idiosyncratic Shocks

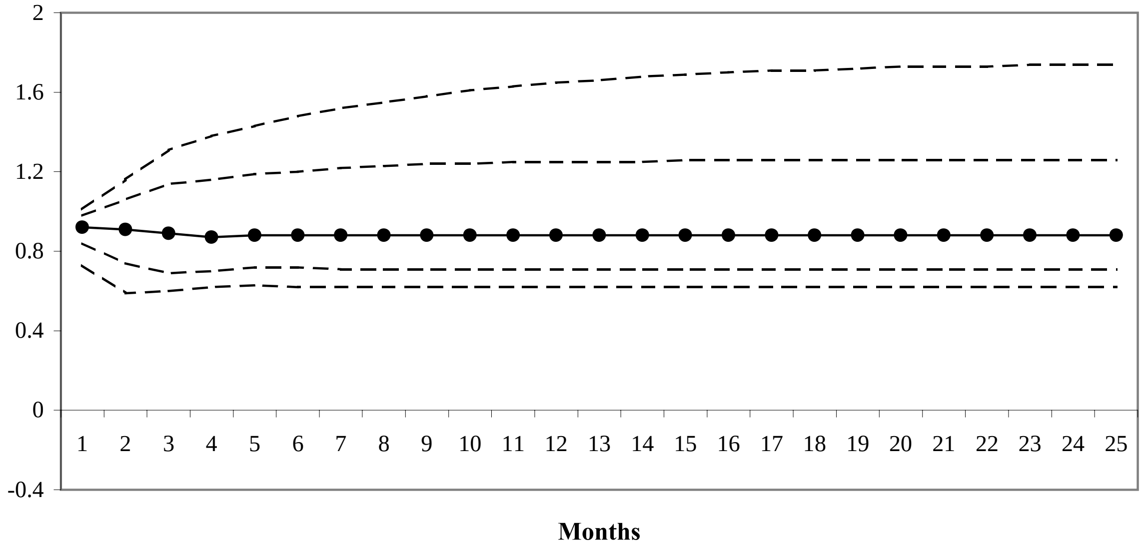


Figure 4: Impulse Responses to a Common Shock

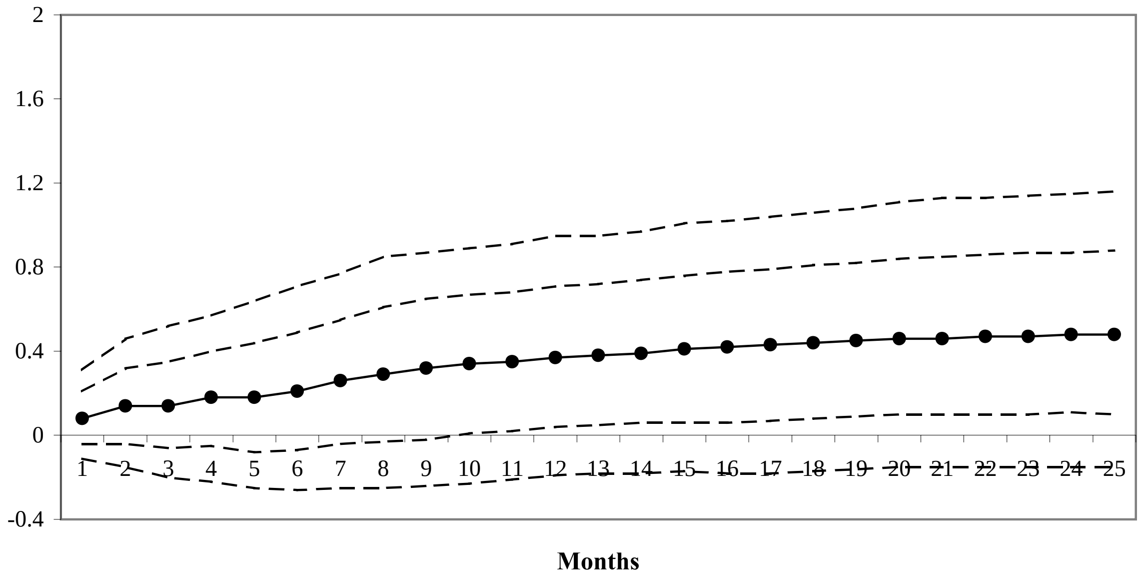


Figure 5: Impulse Responses to a Monetary Policy Shock, based on McCallum and Smets (2008)

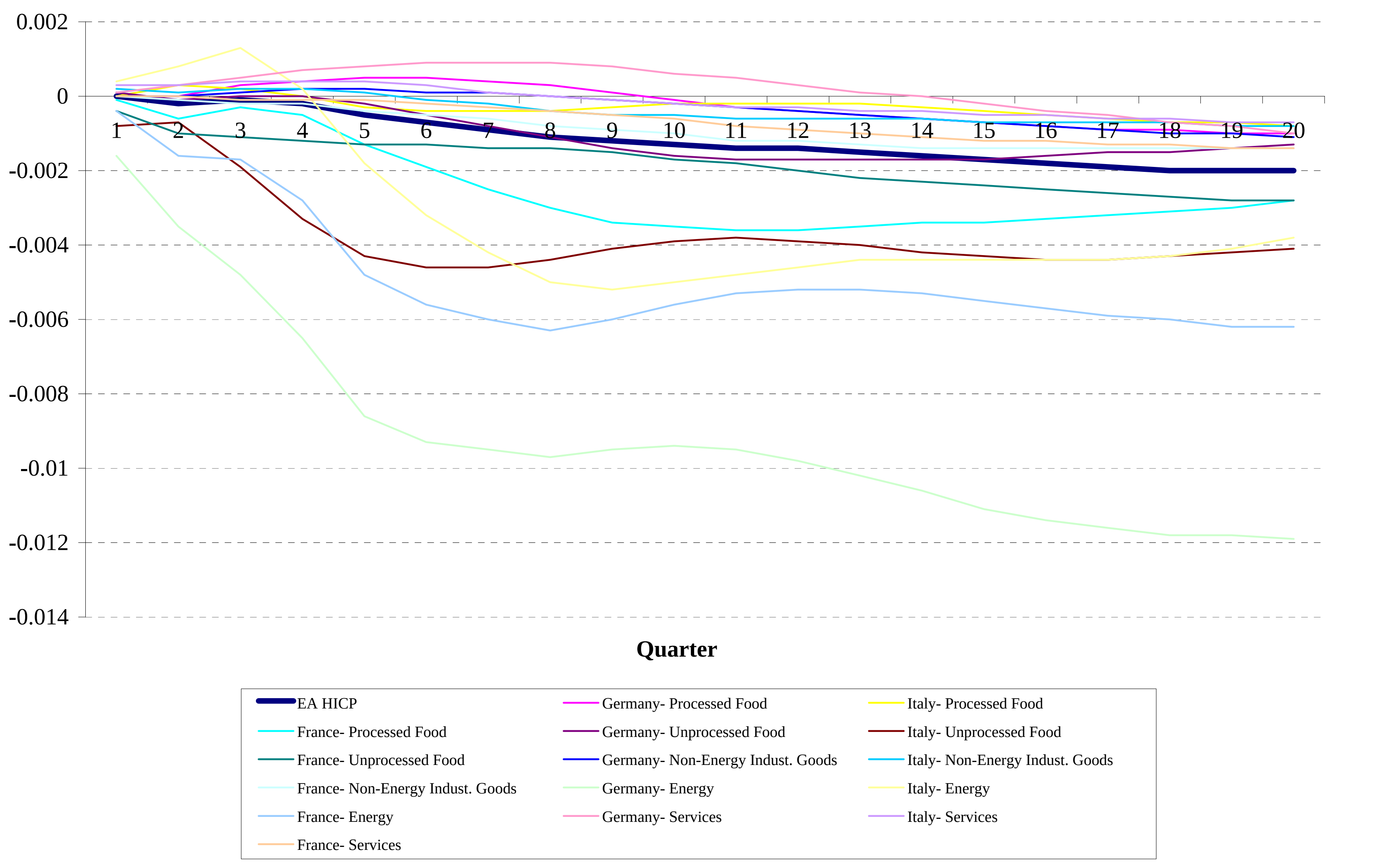


Figure 6: Impulse Response to a Monetary Policy Shock vs. Frequency of Price Changes, based on McCallum and Smets (2008)