Evaluating Microfoundations for Aggregate Price Rigidities: Evidence from Matched Firm-Level Data on Product Prices and Unit Labor Cost.*

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Abstract

We analyze data on product-level prices matched to the producing firm's unit labor cost. The data reject the hypothesis of a full and immediate pass-through of marginal cost onto prices. Since we focus on idiosyncratic variation, this does not fit the predictions of the Maćkowiak and Wiederholt (2008) version of the Rational Inattention Model. Neither do we find that firms react strongly to predictable marginal cost changes, as expected from the Mankiw and Reis (2002) Sticky Information Model. We do find that firms consider both current and future expected marginal cost when setting prices. The estimated parameters are well in line with aggregate estimates from Staggered Contracts models and consistent with a full long-run pass-through of marginal cost onto prices.

Keywords: Price Setting, Business Cycles, Information, Micro Data.

JEL classifications: D8, E3, L16.

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1 Introduction

Recently a set of competing business cycle models has emerged that all can explain why nominal shocks have real effects.[1] Although sharing a lot of common features, a key difference between these models lies in the assumptions of how firms set prices and process information. Yet, there exist very little direct micro evidence on the credibility of these assumptions. This paper uses detailed data on product prices and unit labor cost merged at the firm level to evaluate competing sets of assumptions regarding firms' price-setting behavior. We thereby provide evidence on the empirical relevance of the microfoundations of different DSGE models.

The bulk of recent research on aggregated fluctuations focuses on staggered contracting on the micro level, and the implied forward looking price-setting behavior, building on the work by Fischer (1997), Taylor (1980), Calvo (1983) and others. The supply block of this work-horse macro model, rests on a firm-level pricing equation relating the optimal reset price to a discounted sum of today's and future expected marginal cost.[2] Aggregating across firms yield the New Keynesian Phillips Curve which relate inflation to expected inflation and (aggregate) real marginal cost.[3]

Recently, a literature has emerged centered around the idea of Phelps (1970), first formalized by Lucas (1972), that real effects of nominal disturbances stems from imperfect information. In a proposal to replace the New Keynesian Phillips Curve, Mankiw and Reis (2002) suggest that information, rather than prices, is sticky. In their model, a firm updates its information set with a fixed probability each period and, when updating, decides upon a price path which will remain in place until the next time information is received. Thus, nominal disturbances have real effects not due to price staggering, but due to information staggering.

Maćkowiak and Wiederholt (2008) propose a third alternative model, building on work by Sims (1998, 2003), where (some) information also disseminates slowly. Again, prices can be changed freely by the firm in any period, but the firm faces a constraint on the amount of information that can be processed in each time period. This forces

[1] As indicated by a large empirical literature, see e.g. Christiano, Eichenbaum, and Evans (1999) and references therein.

[2] See e.g. Smets and Wouters (2003), Christiano, Eichenbaum, and Evans (2005), Adolfson, Laséen, Lindé, and Villani (2008) and others for examples of the work-horse model.

[3] See e.g. Woodford (2003) for a detailed derivation.

the firm to make an (optimal) choice about the relative attention to pay to idiosyncratic versus aggregate conditions based on the relative volatility of these conditions. In the Maćkowiak and Wiederholt (2008) version of the "Rational Inattention Model" the firm allocate almost all attention to idiosyncratic conditions. This gives rise to a situation where firms react as strongly and as quickly to idiosyncratic conditions as if they had perfect information (i.e., as in a frictionless model). In contrast, firms react in a damped and delayed fashion to aggregate conditions, again giving rise to real effects from aggregate nominal disturbances.[4]

Although all of the models above can explain why nominal shocks give rise to real effects, they do differ in their lessons for monetary policy, see Reis (2008) or Maćkowiak and Wiederholt (2008) for a discussion. Thus it is important to collect evidence on which set of microfoundations (if any) is in line with the data. The key novelty in this paper is that we evaluate the empirical relevance of these different microfoundations directly at the micro level. We do this using very detailed Swedish data on product producer prices matched to a rich data set containing information on the activity of the firms that set these prices. Using our firm-level data, we construct a measure of marginal cost (i.e., unit labor cost), consistent with the bulk of macro models in the literature. This is, to our knowledge, the first time such detailed quantitative price data has been merged with detailed information on firm-level activity for a broad sample of firms.[5] The matched data set contains $17,282$ price observations (with at least a spell length of two periods) across $1,610$ unique product codes, $3,510$ unique product/firm identities produced by 702 industrial firms.[6] These firms are mainly medium to small firms with an average of 65 employees.

Since marginal cost is unlikely to be exogenous, we use Instrumental Variable (IV)-/Generalized Methods of Moments (GMM) methods. Beside internal instruments (i.e. lags) we also exploit variations in factor market conditions between competing firms using data on all Swedish employment spells in the private sector matched with detailed characteristics of each individual employee. To obtain an instrument that is correlated with the firms' marginal costs, but unrelated to the firms' decisions, we use regional

[4] In related work, Woodford (2002) propose a model in which the firms face a signal-extraction problem where they pay little attention to aggregate conditions.

[5] Lundin, Gottfries, Bucht, and Lindström (2007) uses a similar Swedish data set (but with a plant-level producer price index instead of individual product prices) to estimate a customer-markets model.

[6] The industrial sector constitutes about 30 percent of total private sector GDP in Sweden.

variation in predicted wages over time for workers with different skills to derive the market valuation of the (lagged) skill composition of each firm.

Using IV/GMM methods and focusing on idiosyncratic variation,[7] we find that the data forcefully reject the text-book hypothesis that the firm should set its price as a markup over marginal cost with an immediate and full pass-through. Instead we find a price-cost elasticity of about one third. This incomplete adjustment to idiosyncratic marginal cost changes are also inconsistent with the Maćkowiak and Wiederholt (2008) version of the Rational Inattention Model, which predicts a full and immediate price response to idiosyncratic movements in marginal cost. The result is, on the other hand, consistent with nominal frictions such as in a Staggered Contracting Model. We then proceed by estimating the Calvo (1983) pricing equation, which is the key underlying pricing relationship in the work-horse macro model. We find that the data do support that firms consider both current and future marginal cost when setting prices. Furthermore, the estimated parameters are well in line with implications from estimated aggregate models relying on staggered prices (e.g. Adolfson, Laséen, Lindé and Villani, 2008, or Smets and Wouters, 2005), as well as, being in line with a full long-run pass-through of marginal cost onto the price. The lack of full pass-through of marginal cost onto prices is also consistent with the Mankiw and Reis (2002) Sticky Information Model, since this model assumes that firms are not fully aware of their current marginal cost, except when drawn to update their information set. To test the Mankiw and Reis (2002) Sticky Information Model we rely on their baseline calibration of the information-stickiness parameter to determine the fraction of informed firms. However, we do not find that firms react strongly to marginal cost changes that could have been predicted by the vast majority of information vintages of firms. In fact, lagging the instruments set backwards does not affect the point estimates of the pass-through of marginal cost onto the price to any noticeable extent. Thus, the data does not support the idea that information is sticky in the Mankiw and Reis (2002) sense.

This paper is organized as follows: Section 2 discusses related literature. Section 3 outlines the various price-setting models we consider. Section 4 describes the data and discuss our empirical strategy and Section 5 reports the results. Finally, section 6

[7] That is, we include sector-specific time dummies and look at the relative price reactions to idiosyncratic variation in marginal cost.

concludes.

2 Related Literature

Considerable effort has been put into studying the macro-implications of staggered contracts and evaluate the empirical performance of the New-Keynesian Phillips curve. See e.g. Galí and Gertler (1999), Galí, Gertler, and López-Salido (2001), Lindé (2005) and Sbordone (2002), and in a full system setting e.g. Smets and Wouters (2003), Christiano, Eichenbaum, and Evans (2005) and Adolfson, Laséen, Lindé, and Villani (2008). Overall, the New Keynesian Phillips curve seem to provide a reasonable account of inflation dynamics, although whether a hybrid version with backward looking as well as forward looking terms is needed is still an open issue.

Mankiw, Reis, and Wolfers (2003) finds evidence in support of the Sticky Information Model using survey data on inflation expectations. However, Coibion (2007) tests the empirical relevance of sticky prices relative to sticky information on macro data and find that the Sticky Information Phillips Curve, conditional on historical inflation forecasts, is statistically dominated by the New Keynesian Phillips Curve. There exist, however, little empirical work on evaluating the Rational Inattentions Models since the achievement of Maćkowiak and Wiederholt (2008) to incorporate a rational intention mechanism into a DSGE setting is very recent. Boivin, Giannoni, and Mihov (2007) present US sectoral and aggregate evidence that supports the Maćkowiak and Wiederholt (2008) model by finding a fast reaction to sectoral shocks, but prolonged responses to aggregate shocks. Maćkowiak, Moench, and Wiederholt (2008) also report a fast response of sectoral prices to a sectoral disturbance, in contrast to a prolonged response stemming from an aggregate disturbance.

On the micro side, research has been focused on the behavior of price adjustment for particular products in terms of the size and the frequency of price changes or the duration of fixed price spells and its implications for different models of price setting; see e.g. Bills and Klenow (2004), Klenow and Kryvtsov (2008), Nakamura and Steinsson (2008), Álvarez, Dhyne, Hoeberichts, Kwapil, Le Bihan, and Lunnemann (2006), Dhyne, Álvarez, Le Bihan, Veronese, Dias, Hoffmann, Jonker, Lunnemann, Rumler, and Vilmunen (2006), Vermeulen, Dias, Dossche, Gautier, Hernando, Sabbatini, and Stahl

(2007) and others. Another strand of the literature has been focusing on asking firms about their price-setting practices in surveys, see e.g. Blinder, Canetti, Lebow, and Rudd (1998), Apel, Friberg, and Hallsten (2005), Druant, Fabiani, Kezdi, Lamo, Martins, and Sabbatini (2008), Fabiani, Druant, Hernando, Kwapil, Landau, Loupias, Martins, Mathä, Sabbatini, Stahl, and Stokman (2006) and others. Although informative regarding firm price-setting behavior in general, results from these studies cannot fully discriminate between the different sets of proposed microfoundations since one dimension of the problem is missing. Due to the lack of linked data sets, very few papers have managed to relate the cost that an individual firm faces to the prices set by these firms. Two exceptions are Buckle and Carlson (2000) and Loupias and Sevestre (2008), although these studies rely on qualitative price and cost information (up, same, down, or more elaborate), thus restricting the analysis to estimating ordered probits.[8,9]

The key novelty in this paper is that quantitative price data on the product level has been merged to information on the producing firm's production level, inputs and costs. The frequency of the data is annual, so we are unable to study the exact duration of price spells, but we do see a relatively high frequency of price spells with a duration above one year in the data. The quantitative nature of the data imply that we can study the size of the pass-through of marginal cost onto the price and to what extent past expectations of current outcomes, or current expectations of future outcomes, matter for pricing decisions.

3 Theory

If the firm, indexed by subscript f, has any price-setting power in the product market, the optimal frictionless price at time t, $P_{f,t}$, is set as a markup, $\mu_{f,t}$, over marginal cost, $MC_{f,t}$, i.e.[10]

$$P_{f,t} = \mu_{f,t} MC_{f,t}. \tag{1}$$

[8]It should be noted that Loupias and Sevestre (2008) merge their data with quantitative information on average firm-level base wages as well.

[9]There is also a micro-data literature relating retail prices to costs (wholesale/spot prices for the vended product), see e.g. Levy, Dutta, and Bergen (2002), Davis and Hamilton (2004) and Eichenbaum, Jaimovic, and Rebelo (2008), or, taking a broader perspective, looking at detailed PPI or CPI data for components with a low value added and constructing input cost using an input-output table, see e.g. Peltzman (2000).

[10]For expositional ease, we initially assume that the firms only produce a single product.

Moreover, since cost minimization implies that, at the optimum, the cost associated with each possible margin of adjustment should be the same, it is sufficient to only look at one of them. Here we focus on the labor-input margin. Marginal cost can then be written as

$$MC_{f,t} = \frac{\partial Cost_{f,t}}{\partial L_{f,t}} \frac{\partial L_{f,t}}{\partial Y_{f,t}}, \tag{2}$$

where $L_{f,t}$ denotes labor input. Following Bils (1987), Rotemberg and Woodford (1999) and others, we assume the following production function

$$Y_{f,t} = (Z_{f,t} L_{f,t})^{\alpha} g(Other\ Factors\ of\ Production_{f,t}), \tag{3}$$

where $Z_{f,t}$ denotes labor augmenting technical change.[11] Given expression (3), equation (2) can be rewritten as

$$MC_{f,t} = \frac{\partial (Wage\ Bill)_{f,t}}{\partial L_{f,t}} \left(\frac{1}{\alpha} \frac{L_{f,t}}{Y_{f,t}} \right). \tag{4}$$

Then, assuming that firms are wage takers in the local labor market and denoting the average wage (across the skill composition of the employees) for firm f at time t as $W_{f,t}$, we arrive at

$$MC_{f,t} = \frac{1}{\alpha} \frac{W_{f,t} L_{f,t}}{Y_{f,t}} = \frac{1}{\alpha} \frac{(Wage\ Bill)_{f,t}}{Y_{f,t}}, \tag{5}$$

showing that marginal cost is proportional to unit labor cost.

Taking logs, and assuming that the firm faces an iso-elastic demand function, we arrive at the frictionless model, where we now allow for firms selling several products, as in the data, by introducing the index g which index unique products by firm f

$$\ln P_{g,t} = \gamma_g + \ln MC_{f,t}, \tag{6}$$

where γ_g is the log of the, possibly product-specific, time invariant markup.[12] Note that marginal cost movements will have an immediate and full pass-through onto prices in the frictionless model.

[11] Note that this production function is slightly more general then a Cobb-Douglas.

[12] Here we need to assume that the marginal cost is the same across all products. Since this may not be true, this will provide a source of error in the empirical implementation. However, since we will employ an IV-approach in the empirical work this problem should be of minor importance.

Maćkowiak and Wiederholt (2008) outline a model where prices can be changed freely in any period, but the firm faces a constraint on the amount of information that can be processed at each point in time. This forces the firm to make an choice about the relative attention to pay to idiosyncratic versus aggregate conditions based on the relative volatility of these conditions. Maćkowiak and Wiederholt (2008) calibrates their model to match micro-evidence on prices (i.e. the average absolute size of price changes) resulting in an outcome where firms allocate 96 percent of their attention to idiosyncratic conditions. This gives rise to firms reacting as strongly and as quickly to idiosyncratic conditions as if there was perfect information. In contrast, the firm reacts in a damped and delayed fashion to aggregate conditions. Thus, the firm's reaction is very much dependent on the type conditions that has changed. To take this prediction to the micro data we estimate the empirical version of (6) to see if the parameter on $\ln MC_{f,t}$ is close to unity when we let sector specific time dummies remove all but the idiosyncratic movements from the analysis. Removing all sectoral movements implies that we look at relative-price responses to idiosyncratic movements in marginal cost.

In the recent macroeconomic literature, the dominant paradigm for thinking of the relationship between price setting and marginal-cost dynamics is Calvo (1983) style nominal rigidities. In the Calvo model, the firm is allowed to reset the price with probability $(1-\theta)$ each period, whereas it is stuck with the old price with probability θ. The firm's first-order condition in a Calvo-economy is

$$\ln P_{g,t} = \gamma_g + (1-\theta\beta)E_t \sum_{k=0}^{\infty} (\theta\beta)^k \ln MC_{f,t,t+k}, \tag{7}$$

where $P_{g,t}$ is the optimal reset price for the firm at time t, and γ_g again is the log of the firm's (product specific) markup.[13] Moreover, β is the discount factor and $E_t MC_{i,t,t+k}$ denotes the expectation taken at time t of (nominal) marginal cost of firm i at time $t+k$ when the price was last reset at time t. Thus, the price is set as a markup over the weighted average of the discounted stream of marginal costs, where the weight on the k:th term reflects the probability of being stuck with the reset price $P_{i,t}$ for k periods ahead. Note that in the limiting case of complete price flexibility ($\theta \to 0$), price will just be a markup over current marginal cost, i.e. (7) converges to expression (6). Thus, the

[13] See e.g. Galí, Gertler, and López-Salido (2001).

future only matters if there are impediments to continuos price adjustment.

Mankiw and Reis (2002) suggest instead that information (rather than prices) is sticky due to intermittent information updating. In the Mankiw and Reis (2002) Sticky Information Model, a firm update its information set with a fixed probability each period and then, when updating, decides upon a price path which will remain in place until the firm is drawn to update the next time. The firm's optimal price in period $t+k$ is then given by

$$\ln P_{g,t+k} = \gamma_g + E_{t-r} \ln MC_{f,t+k}, \tag{8}$$

where $t+k$ denotes period $t+k$ in the firms price plan, $t-r$ is the time period when the information set was last updated, γ_g is the log of the firm's (product specific) markup.[14]

4 Data and Empirical Strategy

The data we use in this paper are drawn from the Swedish "Industrins Varuproduktion" (IVP) survey for detailed product-price data that can be linked to the producing plant, the "Industristatistiken" (IS) survey for information on plant-level activity and, finally, the Register Based Labor Market Statistics data base (RAMS) provides information on each individual employee in each plant, as well as, for all other employees in the private sector.

The IVP survey provides annual information on prices and quantities of products produced for all industrial plants with at least 10 (20) employees for the years $1990-1996$ $(1997-2002)$ and a sample of smaller plants. The product classification is at the finest (i.e., the 8/9-digits) level of the Harmonized System (HS) for the years $1990-1995$ and for the Combined Nomenclature (CN) for the years $1996-2002$. The CN is the EU's coding system for classifying products for customs and statistical purposes. This classification is, in turn, based on the HS, which is also the basis for the import and export codes used in the US.[15] These data are quite unique and it is therefore important to note a few points. First, the (per unit) price data is calculated from yearly reported values and volumes of sold products within each product code stated by the firm.[16] The data are thus based on

[14] See Trabandt (2007) for a discussion on optimal pricing behavior for a firm in a Sticky Information Model.

[15] See the appendix A for more details abut handling this change in coding system and other details.

[16] There is no flag for sales in the data, but as noted by Nakamura and Steinsson (2008) sales seem to be uncommon in producer price data.

actual transaction prices and not list prices, which may behave very differently. Secondly, given the very fine level of classification we can actually follow the same product (or in the worst case scenario, a very closely defined group of products) over time. To see the level of detail at the finest level of the product code it is instructive to look at examples of descriptive texts. As such an example, product code 84181010 refers to "*A combined freezer and cooler with separate exterior doors with a volume exceeding 340 liters intended for use in civilian aircrafts*".

Since the raw price data involves a few very large swings we apply a cleaning procedure for the data used in the final analysis. To remove the impact of this type of observations on the results, we split the individual price series and give them a new unique plant-price identifier whenever a large change in the growth rate appears in the raw data. We use the full raw-data distribution of all price changes that we can match to the firms in the IS data to determine the cut-off levels as given by the 1.5 and 98.5 centiles of this distribution. See Appendix A for more details. There, we also discuss experiments with changing the cut-offs.

A key novelty in this paper is that these data can be matched to data on activity for the individual plant from the IS survey. This survey contains annual information for the years $1990 - 2002$ on inputs and output for all Swedish industrial plants with 10 employees or more and a sample of smaller plants. We only keep plants that are also a firm since pricing essentially is a firm and not a plant-level decision. There may also be scope for transactions between plants within a firm for tax reasons. In addition, we limit the analysis to continuing firms since we want to identify "normal" behavior.

From the IS survey we have information about the firm's wage bill which we will use to construct unit labor cost.[17] Also, from the IS survey we collect our measure of nominal output, defined as the value of total sales. This measure is deflated with a firm-specific producer price index in order to obtain a measure of real output, $Y_{i,t}$. The firm-specific price index we use is a Paasche index, constructed using a combination of the plant-specific unit prices, described above, and the most detailed producer-price indices available. The producer-price index for the relevant class of products is used if the 8/9-digit unit value data is not available due to missing data or changes in the firms product

[17] Throughout the analysis, we focus on the wage bill net of payroll taxes. These taxes are proportional to the wage bill and in our empirical approach we will include a dummy setup that will fully capture the impact of proportional taxes.

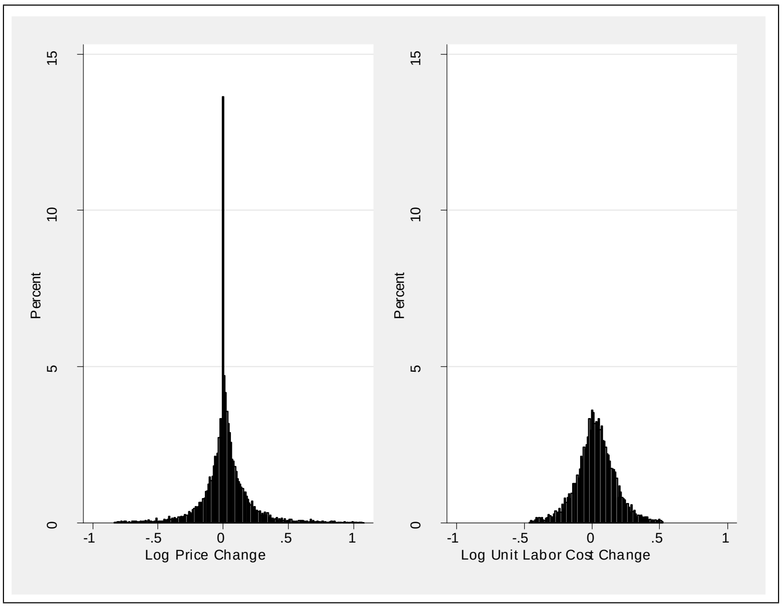

Figure 1: Histograms of final data. Left panel describes the distribution of log price changes across $13,772$ observations (for $1,610$ different products across 702 firms). Right Panel describes the distribution of log unit labor cost changes across $8,424$ observations (for 702 firms). Bin size 0.01.

portfolio, or if the price change is one of the 1.5 percent most extreme price changes observed in any tail of the raw data distribution of log price changes (consistently with how we treated individual price changes above).

After constructing the firm-level variables, we remove firms which are subject to large swings in observed marginal cost. Again, this is done in order to capture normal behavior and not the behavior of firms undergoing extreme circumstances. Similarly, as with prices, we use the full distribution of log changes in unit labor cost across all firms for which we can compute this variable and remove firms which have growth rates outside of the $[1.5, 98.5]$ centiles in any year.

When merging data sets, we are left with $17,282$ price observations (with a minimum spell length of two periods) across $1,610$ unique product codes, $3,510$ unique product/firm identities and 702 firms. These industrial firms are mainly medium to small firms with an average of 65 employees (see the appendix A for more details).

In figure 1, we plot the final data distribution of log price changes (for the 8/9-digit unit value data). All in all, this comprise of $13,772$ price change observations. Each bin represent a log difference of 0.01. Note, that since these prices are calculated from reported values and volumes of sold products, there might be small rounding errors in the data. However, as can be seen in figure 1, there is a substantial spike for the bin centered around zero. In fact, 13.6 percent of the price-change observations are confined within the ± 0.5 percent interval. Thus, implying a considerable amount of very small price changes.

The observation of a quite substantial part of fixed prices across years is well in line with the survey evidence. When surveying 626 Swedish firms in 2002, Apel, Friberg, and Hallsten (2005) found that about 70 percent of the firms adjust their price once a year or less often. Moreover, for the approximately $15,000$ European firms surveyed in the Eurosystem Wage Dynamics Network (WDN), Druant, Fabiani, Kezdi, Lamo, Martins, and Sabbatini (2008) report that about half of the firms change their price once a year or less frequently on average.

The spike at zero gives a first indication of the presence of price rigidities. However, the observation of fixed price spells is not ironclad proof of price rigidities *per se* since marginal cost may not have moved. This is something we turn to below.

The log price-change distribution is right skewed (skewness coefficient of 0.46) and highly leptokurtic (kurtosis coefficient of 8.62).[18] It is also interesting to note that the mean price change in these data is close to the inflation rate computed for the Swedish industry, 1.8 in the sample and 1.9 percent in the aggregate. The median log price change is almost zero, 0.003, however. To look at persistence in the relative prices we run an AR(1) in the log price, while controlling for fixed product effects and the interaction of year and two-digit sector-code (NACE) dummies. This yields a coefficient of 0.546 (with a standard error of 0.234).[19] Thus, pointing towards fairly persistent dynamics in relative prices, but still mean reverting.

In the right panel of figure 1, we plot the distribution of log changes in unit labor cost for the 702 firms (all in all $8,424$ observations). As can be seen in the figure, there is no corresponding spike at zero unit labor cost change.[20] Thus, the data do support the view

[18] Some caution should be observed when interpreting the skewness and kurtosis numbers here since we have manipulated the tails of the raw data distribution.

[19] We use the Arellano and Bond (1991) bond estimator with lagged (2-9) log prices as instruments. We impose the restriction that the relationships in the "first stage" is the same across all time periods, i.e. we collapse the instrument set (see e.g. Roodman, 2006, for a discussion). The standard error is the robust standard error from the first stage. Including the full history in the instrument set does not change the results. Including a second lag yields a small and insignificant point estimate for this additional term.

[20] In fact, there is only 3 observations with exactly zero growth in marginal cost, whereas the corresponding number for price changes is 529.

that the spike in the price-change distribution is an indication of nominal price rigidities. Looking at skewness and kurtosis statistics of the unit labor cost change distribution we see that this distribution is more symmetric (skewness coefficient of 0.01) and much less peaked (the kurtosis coefficient equals 3.82). The mean log unit labor cost change is equal to 0.027 and the median is about 0.025.[21] To study the persistence in relative unit labor cost we run an AR(1) in log marginal cost, while controlling for fixed firm effects and the interaction of year and two-digit sector code dummies. This yields a coefficient of 0.542 (and a standard error of 0.04).[22] Since we found that the relative price was mean reverting it is reassuring to see that relative unit labor cost is also mean reverting. In addition, the dynamics for relative unit labor cost is very similar to that of relative price.

4.1 Instrumentation

To obtain an empirical version of the frictionless model (6), we add a free parameter on the marginal cost term as well as an error term. The error term can be interpreted as a markup shock. Consequently, it will be correlated with marginal cost unless the marginal cost curve is flat. We then need instruments to identify the causal effects of changes in marginal cost on price-setting behavior. Similarly, in order to handle expectations when taking the Calvo and the Mankiw Reis models to the data we will also need to rely on instruments (see section 4.2 below).

One approach which we will employ, is to use internal instruments (i.e. lags of dependent variables). However, we also construct instruments based on local labor market wage variation and the firm-specific labor force composition using data for all employees in the private sector (RAMS) which can be linked to the firm-level data.

For our purposes, it is useful to think of the wage bill as the product of (i) the number of employees across different worker types and (ii) the average market wage for each such type, where each type is defined by a vector of skill characteristics (age, education, etc.).

[21] Note, that since a firm can sell more than one product, these numbers cannot be directly compared to the inflation rates above.

[22] Again, we use the Arellano and Bond (1991) bond estimator with lagged (2-9) log marginal cost and (1-9) of the projected marginal cost as instruments and collapsing the instrument set. The standard error is the robust standard error from the first stage. Including the full history in the instrument set does not change the results. Including a second lag yields a very small point estimate for this additional term.

We thus rewrite the marginal cost measure in (5) as

$$MC_{f,t} = \frac{1}{\alpha} \frac{\mathbb{W}_{j,t}\mathbb{L}'_{f,t}}{Y_{f,t}}, \tag{9}$$

where $\mathbb{W}_{j,t}$ is a (row) vector of wages for different types of workers in the local labor market j from which firm f hires workers. Moreover, $\mathbb{L}_{f,t}$ is a (row) vector where each element contains the number of employees of firm f across these worker types in period t. This marginal-cost measure thus corresponds to the cost of expanding labor input with an unchanged composition of worker types. This is a natural extension of the macro approach outlined by e.g. Rotemberg and Woodford (1999) when thinking about marginal cost measurements in a micro-data setting. The "external" instrument we construct is the cost associated with expanding on the number-of-employees margin while fixing the initial composition of workers, evaluated at local market wages and the initial level of output. To this end, we use the employment composition within the firm observed in November the previous year as well as last years output level.

The data we use to construct local market wages cover the period $1989 - 2002$ and contain information about annual labor earnings for all privately employed workers in Sweden. The raw data was compiled by the Swedish Tax Authority in order to calculate taxes. Data include information on annual earnings, as well as, the first and last remunerated month received by each employee from each firm. Using this information, we can construct a measure of monthly wages for each employee in each of the firms in our sample.[23] Moreover, individual characteristics has been added for each employee. These stem from various databases maintained by Statistics Sweden and include Age, Gender, Education (both four-digit field and three-digit level codes building on ISCED 97) and Immigration Status (by seven regions of origin). Also, since each employment

[23] The data lacks information on actual hours, so to restrict attention to workers that are reasonably close to full time workers we only consider a person to be a full-time employee if the (monthly) wage for November exceeds 75 percent of the mean wage of janitors employed by municipalities. We only include employment spells that cover November since, given labor market flows, we must choose one month to focus on, and given the instrument we want to construct we should focus on a month late in the year. Since December is influenced by Christmas holidays we choose to focus on November (following the practice of Statistics Sweden). Also, we only count an individual as employed by at most one firm each year by only keeping the employment with the highest wage. Thus, in other words, we focus on individuals primary employment. Using a similar procedure with RAMS data, Nordström Skans, Edin, and Holmlund (2006) found that this gives rise to a computed wage distribution that is close to the direct measure of the wage distribution taken from the 3 percent random sample in the LINDA database (see Edin and Fredriksson, 2000).

spell is associated with a firm we, can observe which sector and local labor market the spell pertains to.[24]

To obtain the local market wage in period t as a function of observable characteristics, we estimate the following Mincer-type equations on (log) observed wages for all full-time employees in the private sector for each local labor market in period t

$$\ln W_{l,t} = \Theta \left[\begin{array}{c} Sex_l, Age_{l,t}, Age_{l,t}^2, Age_{l,t}^3, Education\ Level_{l,t}, \\ Education\ Field_{l,t}, Imigrant\ Status_l, Sector_{l,t} \end{array} \right], \tag{10}$$

where l index individual workers. Using $\hat{\Theta}$ we can then obtain the period t local labor-market valuation for each worker cell in the initial distribution. This procedure is then repeated for each year in the sample. We thus use a very broad data-set to estimate the market valuation. Then we check whether the individual firm's degree of monopsony power in the local labor market for a certain cell is a concern. Finally, we divide the projected wage sum by lagged output, which we use as a measure of the initial output level. Thus, we treat lagged output as predetermined. All in all, we can write our instrument, which we label the Projected Marginal Cost, as

$$\widehat{MC}_{f,t} = \left(\frac{\widehat{\mathbb{W}}_{j,t} \mathbb{L}'_{f,t-1}}{Y_{f,t-1}} \right), \tag{11}$$

where $\widehat{\mathbb{W}}_{j,t}$ is a (row) vector of predicted market wages for different cells of worker characteristics in the local labor market j and $L'_{f,t-1}$ is a (column) vector where each element contains the number of employees in period $t-1$ (November last year) for each cell of firm f which operates in local labor market j.[25]

Empirically, we start by estimating the Mincer equation outlined in (10) for each local labor market and year. We thus estimate $1,417$ (13 years by 109 local labor markets) Mincer equations. The number of full-time primary employments in the private sector covering November, ranges from $1,499,285$ employed individuals in the recession year 1993 to $2,056,509$ employed individuals in 2001. For each year and local labor market we regress the log observed monthly wages on age, age squared, age cubed, sex, two-digit sector-code (NACE) dummies, two-digit education-level (ISCED 97) dummies, three-

[24] We use a definition of homogenous local labor markets constructed by Statistics Sweden using commuting patterns. We use the 1993 definition which divide Sweden into 109 areas.

[25] Note also that we dropped the $1/\alpha$ term, as compared to (9) since this will be picked up by fixed effects.

digit education-field (ISCED 97) dummies, immigrant-status dummies for seven different regions of origin, and finally, for missing education information we also create interaction dummies for this category with immigrant status by origin.

We then project period t wage sums for each firm by using the characteristics of the employees working in the firm in period $t-1$ (i.e. November last year) and the characteristics-specific wage predictions from the (j,t) Mincer equation. Since no firm in the sample employs more than 3.2 percent of the total number of workers within a specific education cell, defined by two-digit level by three-digit field code, in any local labor market at any point in time, monopsony power in the local labor market does not seem to be a concern. Finally, as presented in more detail in Appendix B, we do seem to get the projected wage sums right. Also the projected marginal cost measure (11) is strongly correlated with unit labor cost, even when we control for sector-specific time effects and firm-specific fixed effects. Thus, there is variation in the dimensions needed to identify the firm-level effects from marginal cost on prices (again, see Appendix B for details).

4.2 Taking the Models to the Data

In this section we discuss how to take the models to the data, combining the discussion above with other identification issues that we need to consider.

Empirical considerations for the Frictionless Model and the Maćkowiak and Wiederholt (2008) Model

To test the frictionless hypothesis we introduce a free parameter λ on the marginal cost term in equation (6), which we expect to equal unity in the absence of any frictions, as well as adding an error term to this equation. As discussed above, since we expect the error term in this regression to be correlated with marginal cost, we use projected marginal cost (current and lagged), as well as, (lagged) unit labor cost as instruments. We thus rely on the following moments

$$E_t\{(\ln P_{g,t} - \gamma_{g,0} - \lambda \ln MC_{f,t})\mathbb{Z}_{FM,t}\} = 0. \tag{12}$$

to estimate the λ, where $\mathbb{Z}_{FM,t}$ denotes the instrument set discussed above. Finally we also include sector-specific time dummies. Given this, estimates of λ also provides a test of the prediction from the Maćkowiak and Wiederholt (2008) Rational Inattention Model that firms will react strongly to idiosyncratic conditions. Here, we interpret this prediction as λ being close to unity.

Empirical Considerations for the Calvo (1983) Model

To take the Calvo (1983) model (7) to the data we need to handle a series of complications. First, (7) include an infinite sum of current and future marginal cost. However, the terms in this sum falls to zero. Using the quarterly aggregate estimate of $\theta = 0.84$ reported by Adolfson, Laséen, Lindé, and Villani (2008) for domestic Swedish firms and likewise assuming that $\beta = 0.99$, we will expect a coefficient on current marginal cost in annual data of 0.52.[26] Similarly the coefficient for $E_t \ln MC_{f,t,t+1}$ will be 0.25, and for $E_t \ln MC_{f,t,t+2}$ we will have a coefficient of 0.12. Given that the coefficients will be falling fairly rapidly towards zero, we truncate the sum in (7) to $k \in \{0, 1\}$ in our empirical application. We also need to condition the regression on firms that actually change their price since (7) expresses the optimal reset price. We then rely on observations where $d \ln P_{g,t} \neq 0$ by excluding observations of very small price changes (below ± 0.5 percent) from the estimation sample.[27] Moreover, we need to handle the expectations operator in the $k = 1$ term in (7). Here, we follow Galí and Gertler (1999) and Galí, Gertler, and López-Salido (2001) and define $\mathbb{Z}_{CM,t-n}$ as a matrix of variables observed in time $t - n$ and note that under rational expectations equation (7) and the assumptions above define a set of orthogonality conditions[28]

$$E_t\{(\ln P_{g,t} - \gamma_{g,0} - \gamma_1 \ln MC_{f,t} - \gamma_2 \ln MC_{f,t+1})\mathbb{Z}_{CM,t-n}\} = 0. \tag{13}$$

Using the orthogonality conditions (13), we can estimate the model using generalized methods of moments (GMM). However, we also need to recognize that the instruments need to be orthogonal to any contemporaneous markup disturbance. Thus, we use lagged

[26]The coefficient on current marginal cost is calculated as $(1 - (0.84 \cdot 0.99)) \cdot (1 + (0.84 \cdot 0.99) + (0.84 \cdot 0.99)^2 + (0.84 \cdot 0.99)^3) = 0.52$. Thus, thinking of annual data as mid-year realizations. Note though that it is not obvious how to assign quarterly coefficients to annual coefficients.

[27]Remember that since the prices are calculated from reported values and volumes of sold goods there might be small rounding errors leading to too few zero observations in the data.

[28]Note that, in order to save on data, we use the unconditional future outcome of marginal cost in the empirical implementation. This should not be problematic if the marginal cost curve is fairly flat, as indicated by the results presented below.

information as instruments. Moreover, since the panel is short we will use an Arellano and Bond (1991) GMM estimator with a dynamic instrument matrix in order to save on data. The Arellano and Bond (1991) estimator involves differencing the levels equation and instrumenting with lagged levels.[29] This, then, in turn, implies that we introduce a MA structure in the errors which need to be considered when deciding upon which lags to include. However, the start point of the instrument set will be determined after formal testing of the time dependence in the error terms. Also, the truncation of the sum in (7) to $k \in \{0, 1\}$ implies that there will be components in the error term that are correlated with all lagged information as far as the expectation of marginal cost in period $t + 2$ and beyond are correlated with the lagged information included in the instrument set. In section 5 below, we take steps to address this potential problem. Finally, we also include sector-specific time dummies in (13).

Empirical Considerations for the Mankiw and Reis (2002) Model

In the Mankiw and Reis (2002) Model, price is set as stated in (8). Then, again forming moment conditions we get

$$E_t\{(\ln P_{g,t} - \gamma_{g,0} - \gamma_1 \ln MC_{f,t})\mathbb{Z}_{MRM,t-h}\} = 0, \tag{14}$$

where γ_1 is expected to equal unity. Here, the instruments needs to be lagged back far enough to ensure that all cohorts of firms should have been able to update their information sets. Thus, our strategy is to identify γ_1 by using variation in marginal cost that any information cohort of firms should have been able to predict, i.e. by setting an appropriate value on h in (14). Using the calibration of Mankiw and Reis (2002) where the quarterly probability of firms to update their information set is set to 0.25, we expect the fraction uninformed to be about $0.32 (= 0.75^4)$ after one year and 0.03 after three years.[30,31] Again we will use the Arellano and Bond (1991) GMM estimator to save on

[29] Note that when estimating the model in differenced form we actually need to estimate the model on observations where the price changed both today and yesterday in order to identify γ_1 and γ_2. When doing this we assume that the first observation in each price spell is a changed price in order to save on data. Note that the data implies that about 86 percent of prices are changed each period. Also, for initial price observation it is only unobserved previous spells that can contain unchanged prices. Not new spells coming from the introduction of new products (where the price is reset by definition) or spells split by the data cleaning procedure described in Appendix A.

[30] Here we think of annual observation as mid-year observations.

[31] The value of 0.25 the quarterly probability of firms to update their information set is also in line with the empirical evidence in Mankiw, Reis, and Wolfers (2003).

data.[32] Finally, we also include sector-specific time dummies.

5 Results

The Frictionless Model / The Maćkowiak and Wiederholt (2008) Model

We start by testing if there are any frictions in firm-level price setting at all (at least measurable at the annual frequency). We include dummies for the interaction of time and two-digit sector code. Thus, the specification looks at the response of relative prices due to idiosyncratic movements in marginal cost. Also, this ensures that we compare firms acting in similar product markets, but who experience different marginal cost movements since they, e.g., act on different factor markets (i.e., acting on different local labor markets and/or employing a different skill structure). In the first column of table 1 we present OLS

Table 1: Flexible Price Model / Maćkowiak and Wiederholt Model

Dependent Variable: $\ln P_{g,t}$	OLS	IV	IV
$\ln MC_{f,t}$	0.265	0.320	0.334
	(0.019)**	(0.061)**	(0.055)**
Instrument Set:			
$\ln \widehat{MC}_{f,t-j}$		$j=\{0,1\}$	$j=\{0,1\}$
$\ln MC_{f,t-j}$			$j=\{1,2\}$
Hansen J (*p-value*)		0.19	0.45
Number of Observations	$17,282$	$14,067$	$14,067$
Number of Product/Firm ID:s	$3,510$	$3,144$	$3,144$

Superscript * and ** denotes significantly different from zero at the five/one-percent level. Standard-errors clustered on products inside parenthesis. All regressions include time interacted with two-digit sector-code dummies and product fixed effects. Hansen J denotes p-value of the joint test of model specification and instrument validity. IV-estimates computed using the Stata module XTIVREG2, see Schaffer (2007).

results, ignoring any endogeneity problems, indicating a statistically significant (on the five-percent level) price elasticity of marginal cost change onto prices of 0.27. Although significantly larger than zero, the point estimate is also well below, and statistically different from, unity.[33] Using the current and lagged values of the projected marginal cost

[32] Since this involve differencing the model it actually implies that with the fourth lag in the instrument set there is three periods that has passed between when the information set we use and the lag of marginal cost (included in the difference) that we instrument.

[33] Since some firms in our sample sell several different products simultaneously, a possible concern is that error terms for individual products within those firms may be correlated. This would then affect the inference. However, it is not obvious in which dimension to cluster the standard errors. In the main

as instruments, we see in the second column of table 1 that the point estimate increases slightly to 0.32, but still remains well below unity. Thus, using IV methods does not lead to any dramatic changes in results. Although the standard error triples, the result is still significantly larger than zero, and smaller than one, on the five-percent level. One interpretation of this finding is that the firm's marginal cost curve is not very steep, then only leading to a mild bias when relying on OLS.[34] Note also that the IV-approach ensures that possible classical measurement errors in the explanatory variable (or the instrument) is not a source of bias as long as potential errors are uncorrelated between the instrument and the endogenous variable. Thus, in the presence of measurement errors the change in the estimate when using instruments provides an upper bound on the effect of the slope of the firm's marginal cost curve on the estimate. Also, as shown in the third column of table 1, adding the first and the second lag of unit labor cost to the instrument set only changes the point estimate marginally to 0.33 and lowers the standard error slightly.[35]

All in all, we can reject the null that marginal cost changes are fully passed into prices within the year. Moreover, this finding is not readily consistent with the Maćkowiak and Wiederholt (2008) version of the Rational Inattention Model where firms react strongly and immediately to idiosyncratic factors.[36]

The Calvo (1983) Model / The Mankiw and Reis (2002) Model

Next, we turn to estimate the Calvo (1983) model (13) above. As explained above, we use the Arellano and Bond (1991) GMM estimator with a dynamic instrument set that grows over time as further lags of the instruments become available. Relying on the Arellano and Bond (1991) autocorrelation test of the differenced residual, as well as the Hansen test of the overidentifying restrictions, we start the instrument set at the second lag of the projected marginal cost and at the third lag of marginal cost. To avoid overfitting,

results we have clustered on each product within a firm (allowing for an arbitrary error-term pattern within observations for a product), but we address this issue in more detail in Appendix C.

[34] Since the bias in the OLS estimate appears to be negative the results suggest that marginal cost is negatively correlated to the markup shock implying that the firms marginal cost curve is (mildly) upward sloping.

[35] As can also be seen in table 1, the Hansen test of the overidentifying restrictions cannot reject the null of a correctly specified model and valid instruments for any of the two IV specifications.

[36] One potential concern is that the Maćkowiak and Wiederholt (2008) Model is calibrated for US data. However, the impulse-responses of output and inflation to a monetary-policy shock estimated by Adolfson, Laséen, Lindé, and Villani (2008) using Swedish data is in line with the "conventional wisdom" for the US of a maximum impact after one to one and a half year, thus pointing towards a considerable similarity between the two economies. Moreover, figure 1 gives witness to a substantial volatility on the micro level, as also recorded for the US.

we collapse the instrument set. That is, we impose the restriction that the relationships in the "first stage" are the same across all time periods (see e.g. Roodman, 2006, for a discussion). Then we add lags until the estimates stabilize. Using this procedure we find that we can cut the instrument set at the ninth lag. However, results are robust to including the full available history of instruments. Also, as discussed above, we only include observations where the prices actually change. The first-step GMM results are presented in table 2. As can be seen in the first column of table 2, both the current and

Table 2: Calvo Model / Mankiw and Reis Model

Dependent Variable: $\ln P_{g,t}$	DIFF GMM	DIFF GMM	DIFF GMM	DIFF GMM
$\ln MC_{f,t}$	0.442	0.562	0.327	0.296
	$(0.154)^{**}$	$(0.165)^{**}$	$(0.132)^{*}$	$(0.130)^{*}$
$E_t \ln MC_{f,t+1}$	0.279	0.364		
	$(0.133)^{*}$	$(0.154)^{*}$		
Only Firms Adjusting Price	*Yes*	*Yes*	*No*	*No*
Instrument Set (Collapsed):				
$\ln \widehat{MC}_{f,t-j}$	$j = \{2, ., 9\}$	$j = \{3, ., 9\}$	$j = \{3, ., 9\}$	$j = \{4, ., 9\}$
$\ln MC_{f,t-j}$	$j = \{3, ., 9\}$	$j = \{4, ., 9\}$	$j = \{3, ., 9\}$	$j = \{4, ., 9\}$
AR(2) (*p-value*)	0.00	0.00	0.00	0.00
AR(3) (*p-value*)	0.07	0.06	0.05	0.05
AR(4) (*p-value*)	0.28	0.20	0.66	0.68
Hansen J (*p-value*)	1.00	1.00	1.00	0.00
Number of Observations	10,141	10,141	13,772	13,772
Number of Firms/Products	3,106	3,106	3,510	3,510

Superscript * and ** denotes significantly different from zero at the five/one-percent level. All regressions include time interacted with two-digit sector-code dummies and product fixed effects. The estimation is performed using the Arellano and Bond (1991) generalized method of moments difference estimator computed by the Stata module XTABOND2, see Roodman (2006). One-step coefficents with robust standard errors in parenthesis (clustered on products). AR(x) denotes the p-value for the test of x-order autocorrelation in the differenced residuals. Hansen J denotes p-value of the joint test of model specification and instrument validity from the second-step estimator.

the expected marginal cost enters significantly on the five-percent level. Interestingly, the point estimates, 0.44 for current marginal cost and 0.28 for expected marginal cost is close to what would be expected when combining the structural equation of the optimal price in the Calvo model with the estimate of the aggregate quarterly probability of no price adjustment (θ) of 0.84 from Adolfson, Laséen, Lindé, and Villani (2008). In that case we would expect coefficients of 0.52 and 0.25, respectively, for the current and the expected marginal cost. Moreover, using the US (Euro Area) estimate for θ of 0.87 (0.90) presented by Smets and Wouters (2005) we would expect coefficients of 0.45 (0.37) and 0.25 (0.23), respectively, for the current and the expected marginal cost. In fact, the joint hypothesis of equality between the micro estimates and the expected values, derived from any of the macro estimates mentioned above, cannot be rejected in a formal test on any reasonable level of significance.[37]

To investigate if the truncation bias, discussed above, is a severe problem we take two different steps. First, we lag the instrument set one additional period backwards in time. This further strengthens the results yielding a coefficient on current marginal cost of 0.56 and a coefficient on expected marginal cost of 0.36 with only slightly higher standard errors as compared to the baseline results. Thus, if anything, the truncation bias seems to work against finding significant results in the baseline case. Secondly, we try to include a $E_t \ln MC_{f,t+2}$ in (13). Since there is a problem with passing the AR(3) test we then use the same instrument set as in the previous exercise. We still find positive and significant estimates for $\ln MC_{f,t}$ and $E_t \ln MC_{f,t+1}$ at the five-percent level although the estimates for $E_t \ln MC_{f,t+2}$ is also positive, it is not significant on the five-percent level. All in all, the truncation of the sum in the Calvo model does not seem to be a problem empirically.

Note also that these estimates imply a substantial pass-through of marginal cost onto the price. The estimates imply a price elasticity of 0.72 (with a s.e. of 0.22) with respect to a permanent increase in marginal cost (0.93, with a s.e. of 0.25, if we lag the instrument set one additional period). Thus, we cannot statistically reject a full long-run pass-thorough of marginal cost onto the price on the five-percent level. Note also, that since we estimate a truncated version of the Calvo model, we expect the point estimates to sum to a value a bit below unity even though the model implies a full long-run pass-through of marginal cost.[38] Thus, the point estimates are well in line what we expect under a full long-run pass-through of prices as implied by the Calvo model.

To cross-check our approach, we have also calculated the implied quarterly Calvo probability, θ, of being stuck with the old price directly from the share of unchanged prices in the data. Note, that to observe an unchanged price, we need the price to be fixed for eight quarters. Defining the share of unchanged prices as the share of price changes within the ± 0.5 percent interval then implies a Calvo probability of 0.78 and expected coefficients of 0.64 and 0.23 for $\ln MC_{f,t}$ and $E_t \ln MC_{f,t+1}$, respectively.[39,40]

[37] This is also the case if we use the estimates from the second column of table 2 discussed below

[38] See the discussion in 4.2 of the Calvo model.

[39] θ is given as the solution to $\theta^8 = 0.136$.

[40] The expected price duration is then 4.5 quarters. At a first glance, this duration might be seen as

Thus, this crude approach give rise to expected values within the range of the results from our econometric approach above.

Next, we turn to the Sticky Information Model of Mankiw and Reis (2002). The idea here is to identify price effects of marginal cost movements that could have been projected by the bulk of all information vintages of firms. In the case that all firms could have projected this variation, we expect a coefficient of unity since it is information that is sticky not prices. However, as can be seen in columns two and three in table 2, the coefficient on marginal cost is almost unchanged as we lag the instrument set further back in time (c.f. also the estimates presented in table 1). We would expect it to tend towards unity in a Mankiw and Reis (2002) world since more and more firms would have the information in their information set and thus being able to react to this variation in marginal cost when making their price plans. Note that, given the probability of having the information set being updated in each quarter of 0.25 and thinking of annual data as mid-year to mid-year observations, the share of firms not having the period $t-3$ outcome of their marginal cost in their information set is only about three percent.[41] Note also that through the columns of table 2 the standard errors for the coefficient on $\ln MC_{f,t}$ barely changes, thus indicating that weak instruments is not the cause of our finding.[42] All in all, the results does not support the Mankiw and Reis (2002) notion that information, rather than prices, is sticky.

6 Conclusions

We use very detailed Swedish micro data on individual product producer prices, linked to a rich matched employer-employee data set containing information on the firms that sets these prices to test the empirical relevance of different proposed microfoundations for pricing used in competing models of business cycles models. We construct a measure

a bit on the high side. For example, Nakamura and Steinsson (2008) reports an duration of about 3 quarters for producer prices in the US. It is important to note, however, that Nakamura and Steinsson (2008) reports quite a bit of heterogeneity across sectors in the frequency of price changes and, in the light of this dispersion, the finding here is by no means extreme.

[41] When we start the instrument set at $t-4$ the relevant time span for calculating the share of uninformed is three years since the model is differenced when estimated.

[42] The Hansen test of overidentifying restrictions rejects the null of valid instruments and a correctly specified model in column four of table 2. However, we do not read to much into this result since it is not consistent throughout specifications (c.f. also table 1). Also, the models subjected to the data in this paper are very stylized and we can be pretty certain that none of them represent the true data generating model. The question at hand is rather if they represent reasonable approximations.

of marginal cost based on unit labor cost which is consistent with the bulk of macro models in the literature and test the hypothesis of no frictions in the pricing decision. Since marginal cost is unlikely to be exogenous, we take an IV/GMM approach in the empirical work. Beside internal instruments, i.e. lags, we exploit that we have access to detailed information on all employees within each firm in the private sector. Relying on this information we construct an instrument based on the market valuation of the (lagged) skill composition of the firm normalized by the lagged production level.

We find an instantaneous price elasticity with respect to marginal cost of about 0.3, i.e. well below the unit elasticity predicted by a frictionless model. Since we include sector-specific time dummies in all regressions, our model studies relative price reactions to idiosyncratic marginal cost changes. Our findings thus speaks against the Maćkowiak and Wiederholt (2008) version of the Rational Inattention Model which predict that firms react strongly and immediately to idiosyncratic movements in marginal cost.

However, the lack of full pass-through of marginal cost movements is consistent with nominal frictions such as staggered contracting and we proceed by estimating the Calvo (1983) pricing equation, which is the key underlying pricing relationship in the standard work-horse macro model. This relationship relates the price set by a firm (when changing price) today to a discounted sum of today's and future marginal cost. Relying on IV/GMM methods and the instruments discussed above, we find that the data do support the assumption that firms consider future marginal cost when setting prices, and the estimated parameters are within the range implied by estimates of an aggregate model relying on staggered contracting, as well as, in line with a full long-run pass-through of marginal cost onto the price.

Another hypothesis that is consistent with not finding a full pass-through of marginal cost onto prices is that firms are not fully aware of their current marginal cost except when drawn to update their information set. That is, information is sticky as in the Mankiw and Reis (2002) Model. However, again relying on IV/GMM methods, we do not find that firms react strongly to marginal cost changes that could be predicted by the vast majority of information vintages of firms as predicted by the Sticky Information Model. In fact, lagging the instruments set backwards does not affect the point estimates of the pass-through of marginal onto the price to any noticeable extent. Thus, data do not support the notion that information is sticky in the Mankiw and Reis (2002) sense.

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Appendix

A Data

The data we use is drawn from the Industri Statistiken (IS) survey for plant-level data, the Industrins Varuproduktion (IVP) survey for the 8/9-digit price data that can be linked to the producing plant and the Register Based Labor Market Statistics data base (RAMS) for data on all employees in the private sector.

The IVP survey provides plant-level information on prices and quantities for the years $1990-2002$ at the finest (i.e. 8/9 digits) level of the Harmonized System (HS) for the years $1990-1995$ and according to the Combined Nomenclature (CN) for the years $1996-2002$. Although these two coding systems are identical only down to the 6-digit level the change means that we have no overlap at the most detailed level between 1995 and 1996 in the raw data. To avoid throwing away too much information, we need to merge spells across these two coding systems while minimizing the risk that we create spells of price observations for non-identical products. We thus take a very cautions approach by only merging price spells for products produced by firms that only produce a single product in 1995 and 1996 and which product code is identical between 1995 and 1996 at the 6-digit level. In the left panel of figure 2, we plot the raw data distributions of log price changes (for 8/9-digit unit value data) for all price changes that we can match to the firms in the IS data (including the merged price spells in 1995/1996). All in all, this comprise of $18,878$ observations for $2,059$ unique product codes and $4,385$ unique product/firm identities across 934 firms. Each bin represent a log difference of 0.01. As can be seen in the figure, there is a substantial spike for the bin centered around zero. About 13.2 percent of the price-change observations are confined within the ± 0.5 percent interval (with 714 observations identically equal to zero, i.e. 3.8 percent). Since the raw price data involves a few quite large swings (Max/Min. in the log price change distribution is $7.08/-7.65$) we apply a cleaning procedure for the data used in the analysis. We are concerned about two types of errors in the price data. First, there may be measurement errors (of some magnitude) which shows up as a zigzag pattern in the growth rate of the price and, secondly, there may be, significant changes of, say, the quality of a product within a 8/9-digit product group which will show up as a large one-period increase in

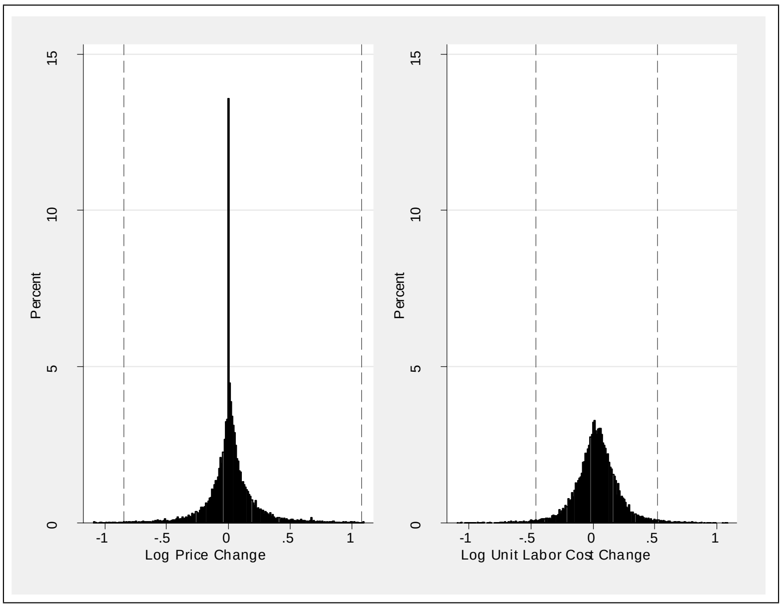

Figure 2: Histograms of raw data of log changes truncated at ± 1.1. Left panel describes the distribution of log price changes across 18,878 observations (for 2,463 different products across 943 firms). Right Panel describes the distribution of log unit labor cost changes across 17,760 observations (for 1,480 firms). Dashed lines indicates truncation limits. Bin size 0.01.

the difference. To remove the impact of this type of observations on the results, we split the individual price series and give them a new unique plant-price identifier whenever a large change in the growth rate appears in the data.[43] We use the full distribution of log price change and determine the cut-off level as given by the 1.5 and 98.5 centiles of this distribution, depicted in the left panel of figure 2. We also correct the firm-specific producer price index used to compute real output in unit labor cost by not using unit-value data in them for these observations. Also, price spells with holes in them are given separate unique plant-price identifiers for each separate continuos spell.

For the data from the IS database we start out with standard data quality checking, removing obviously erroneous observations, like negative sales or zero wage bill. Also, after constructing the firm-level variables we need, we remove firms which are subject to large swings in unit labor cost, since we aim at capturing normal behavior and not firms undergoing extreme circumstances. In the right panel of figure 2 we plot the log changes

[43]This implies that the effect of big zigzag patterns from a one period measurement error in the level of the price will be removed in the estimation since both the initial (the period of the measurement error) and the following observation (and onwards) will have their own fix effect (as well as the observations before the initial period) and whenever there is a large (permanent) drop or hike in the level of prices we allow for different fixed effects before and after the hike/drop.

in firm-level unit labor cost for all firms $(1,480)$ that we can compute this measure for in the IS data, in sum, $17,760$ observations. The distribution is much less spread out as compared to the price change distribution with the Max/Min at $3.52/-3.79$. Similarly, as with prices, we only keep firms that have unit labor cost changes that are inside of the 1.5 and the 98.5 percentile of this distribution in all years (the limits are depicted by dashed lines in the right panel of figure 2).

All in all, this then leaves us with 702 firms that have at least one price spell that is longer than one period. The industrial firms in the sample is dominated by small to medium sized firms with an average of 65 employees. The firms are distributed across 22 two-digit sectors (NACE). The four industries with most firms represented are industry 28 (Fabricated metal products, except machinery and equipment), industry 20 (Wood and products of wood and cork), industry 15 (Food products and beverages) and industry 29 (Machinery and equipment, with together 422 firms (out of the 702). The four smallest sectors industry 14 (Other mining and quarrying products), industry 23 (Coke, refined petroleum products and nuclear fuels), industry 32 (Radio, television and communication equipment and apparatus) and industry 37 (Secondary raw materials) has only one firm.[44]

When experimenting with the cut-of rules for prices and unit labor cost we find that the results presented in tables 1 and 2 in the main text to be robust.[45]

B Evaluating Wage Sum Projections

First, we plot the kernel density of the projected wage sum (obtained using RAMS data) divided by the current nominal value of the production in figure 3 and compare this to the kernel density plot of observed labor shares (computed from the IS data only) for the final sample.[46] As can be seen in figure 3, the two distributions line up very well. It is interesting to see that the two series share almost the same mean (0.21 and

[44] Thus, when including sector-specific time dummies in the regressions these observations will only contribute to the identification of the dummies.

[45] More exactly, we tried a small inward perturbation of the cut-off limits of two percentage points in log-difference space for the price change and an outward perturbation of the unit labor cost change of the same size (where the direction of the perturbation is guided by that the cut-off points is more conservative for the unit labor cost change distribution than for the price change distribution), leaving us with 714 firms and $17,855$ price observations in the final sample.

[46] We need to divide by output, otherwise the figure would mainly reflect the fact that firm size varies and this could potentially mask a week relationship between observed and projected wage sums.

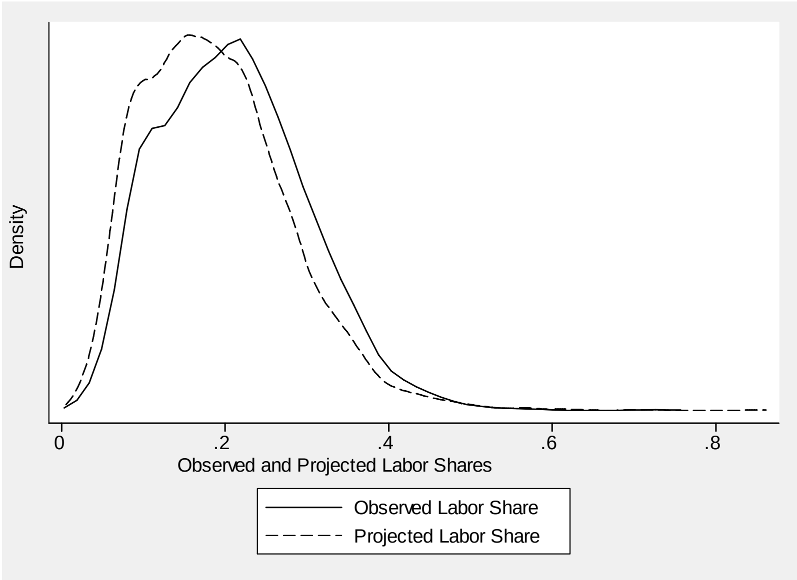

Figure 3: Kernel Density of Observed and Projected Labor Shares. Epanechnikov kernel with a bandwith of 0.013.

0.19, respectively) and standard deviation (0.089 in both cases).[47] Thus, we seem to get the wage sums right. Again, note that the wage sum information is derived from two independent sources (IS and RAMS, respectively). Next, as displayed in table 3,

Table 3: Regressing Marginal Cost on Projected Marginal Cost

Dependent Variable: $\ln MC_{f,t}$	OLS
$\ln \widehat{MC}_{f,t}$ $(= \ln(\widehat{\mathbb{W}}_{j,t}\mathbb{L}'_{f,t-1}/Y_{f,t-1}))$	0.454^{**}
	(0.009)
Number of Observations	8,424

Superscript * and ** denotes significantly different from zero at the five/one-percent level. The regressions include time interacted with two-digit sector-code dummies and firm fixed effects.

we find a very strong relationship when running a regression on observed and projected unit labor cost (i.e., the projected marginal cost), controlling for fixed effects as well as two-digit sector-specific time effects. Also, when including current and lagged projected unit labor cost as instruments in a fixed-effects IV regression of unit labor cost on prices, while controlling for two-digit sector-specific time dummies (c.f. column two in table 1), the null of underidentification is rejected on all significance levels (p-value equal to 0.00)

[47]Note that this is the labor share in gross output and net of payroll taxes.

relying on the Kleibergen-Paap rk LM test (see Kleibergen and Paap, 2006). Also, the first-stage F-statistic of excluded instruments equals 213.57 as opposed to the Staiger and Stock (1997) rule of thumb deeming instruments as weak for first-stage F-values below 10. Thus, the projected unit labor cost seem to work well as an instrument for unit labor cost in terms of relevance.

C Intra-Firm Correlation of Errors

Some of the firms in our sample sell several products simultaneously.[48] Thus, one might suspect that there is a correlation across error terms for individual products within a firm. If so, this cross correlation should be accounted for in the inference. One way to proceed, is to allow for arbitrary patterns of covariances between error terms within a firm by employing a sandwich estimator for the error-term variance-covariance matrix.[49] This is a robust approach since it allows for any type of cross-sectional and time-series dependence, but for the same reasons it is a blunt method which is very likely to yield too large standard errors in finite samples. For the coefficients presented in table 1 standard errors rise, as expected, when using this alternative specification, but still leave all coefficients significant at the one-percent level. For the Calvo and the Mankiw and Reis models standard-errors also increase. In both models though, the p-value for the $\ln MC_{f,t}$ term is below 0.10 across all specifications (corresponding to those presented in table 2).[50] Moreover, for the Calvo model the p-values for the $E_t \ln MC_{f,t+1}$ term stays around 0.10 (with a sequence of p-values of $0.146, 0.118$ and 0.098 as we lag the instrument set further backwards ending at lag $4-9$ for projected marginal cost and $5-9$ for marginal cost).

[48] About one third of the firm/year observations consists of firms selling a single product.

[49] The error-term variance-covariance matrix is then defined as block-diagonal matrix where each block is defined by a firm.

[50] The estimates for the Mankiw and Reis model corresponding to columns 3 and 4 in table 2 are still significantly below unity on all reasonable significance levels.