Price Points and Price Dynamics[1]

Volker Hahn[2] Michal Marenčák[3]

Abstract

We propose a model of price-setting that involves an important role for price points as well as sticky information. It makes empirically reasonable predictions about the frequency of price adjustments, the sizes of price increases and decreases, the shape of the hazard function, the fraction of price changes that are price increases, and the relationship between price changes and inflation. If we integrate our model of price-setting into a small-scale DSGE model, it implies plausible aggregate effects of monetary policy in contrast to a model with a prominent role for price points but no information rigidities.

Keywords: price stickiness; price point; sticky information

E31, E37

[1]We would like to thank Marissa Binz, Matthias Hertweck, Almuth Scholl, Nawid Siassi, participants at the 2016 Doctoral Workshop on Dynamic Macroeconomics at Aix-Marseille University, the ZICE 2016 workshop, the 2016 Spring Meeting of Young Economists in Lisbon, the 2018 meeting of the VfS's committee for monetary theory and policy in Frankfurt, the 2018 ECB Forum on Central Banking in Sintra, seminar participants at the Universities of Konstanz and Nottingham as well as the editor, Yuriy Gorodnichenko, and an anonymous referee for many valuable comments and suggestions. We are particularly grateful to Rowan Kelsoe, the Head of Consumer Prices System Support at the Office for National Statistics (ONS), and his team, who provided us with prompt and detailed answers to numerous questions about the ONS CPI data.

[2]Department of Economics, University of Konstanz, volker.hahn@uni-konstanz.de

[3]Department of Economics and Graduate School of Decision Sciences, University of Konstanz, michal.marencak@uni-konstanz.de

1. Introduction

Understanding the nature of microeconomic price rigidities is central to monetary economics. The leading paradigm in monetary economics, the new Keynesian model, starts from the premise that extended spells of constant prices point to the existence of price-adjustment costs.[4] These costs are considered to be instrumental for rationalizing why monetary policy has real effects.[5] The present paper explores an alternative mechanism that can explain spells of constant prices: price points.

As discussed in more detail in Section 2, there is strong evidence in favor of the relevance of price points, as some prices are chosen much more frequently compared to other prices (see Kashyap (1995), Blinder et al. (1998), Dhyne et al. (2006), Levy et al. (2011) and Chen et al. (2017)). In particular, Knotek (2016) considers a model with traditional menu costs and additional costs that accrue to firms when they choose prices that are not price points. According to his estimation, menu costs are effectively irrelevant as a source of price rigidity. He shows that, as a consequence, monetary shocks have almost no effects on real variables.

The present paper takes a standard model of price-setting under positive trend inflation as a starting point and adds the following two modifications. First, we abstract from menu costs and impose a price-point (PP) restriction, i.e. the requirement that firms can only select prices from a discrete set of price points. Second, because a model with the PP restriction but without additional costs of adjusting prices would have the counterfactual implication that monetary policy is completely ineffective in influencing real variables, we incorporate sticky information as in Mankiw and Reis (2002) into our model.

As a result, our model does not only match the empirical frequency of price adjustment but is also compatible with the empirical regularity that monetary policy affects output and other real variables in the short run as well. While Knotek (2016) analyzes the potential of price points to explain the empirically observed durations of price spells and distribution of price endings, we examine a host of additional implications of our model.

Using a relatively new micro price data set provided by the Office of National Statistics (ONS), we show that most of the stylized facts of price setting documented e.g. by Klenow

[4]Price-adjustment costs are often modeled in a shorthand manner via time-dependent pricing.
[5]See Woodford (2003) for a textbook treatment of the new Keynesian model.

and Kryvtsov (2008) (henceforth: KK) and Nakamura and Steinsson (2008) (henceforth: NS) for the United States hold for the United Kingdom as well.[6] Then we assess the degree to which our approach can explain the empirical evidence for the UK. In particular, we derive the following findings for our main model with a PP restriction as well as sticky information (henceforth: PPSI) and a benchmark model without a PP restriction but sticky prices à la Calvo (1983) (henceforth: SP). Both models are consistent with the following stylized facts: First, three out of four prices stay constant in a quarter. Second, the magnitude of relative price changes is 10% on average. Third, hazard functions are approximately flat and the magnitude of price changes does not increase strongly with the age of the price.

The PPSI model outperforms the SP model along several dimensions: First, the magnitude of price decreases is larger than the magnitude of price increases (Burstein and Hellwig (2007), KK). Second, prices move back and forth between a few rigid values (Eichenbaum et al., 2011; Knotek, 2016).[7] In particular, the PPSI model can reproduce the empirical frequency with which old prices are revisited. Third, the frequency of price increases co-varies with inflation (KK). Fourth, the frequency of price decreases changes less strongly with inflation in comparison (NS). Fifth, the PPSI model is in line with the empirical finding of many small price changes (KK). Sixth, the PPSI model is compatible with a non-negligible role for the extensive margin in explaining inflation fluctuations, while the SP model counterfactually attributes all changes in inflation to the intensive margin.[8]

We also identify a specific implication of the PPSI model. The PPSI model involves that small and large price changes are different in that small price changes are driven by changes in the expected price level, whereas large price adjustments are caused by productivity shocks. Consequently, it predicts that the frequency of small price changes co-varies more strongly with inflation than the frequency of large price changes. We show that this pattern can be found in our data set, which provides additional support for the PPSI model.

[6]For a comprehensive review of the literature on individual price dynamics see Klenow and Malin (2010) and Nakamura and Steinsson (2013).

[7]Eichenbaum et al. (2011) and Matějka (2015, 2016) model firms that follow a price plan consisting of a finite number of points.

[8]KK finds that the extensive margin is almost irrelevant for the variance of inflation in the US. In our data set, we find that more than one third of the inflation variance can be attributed to the extensive margin.

While the focus of our paper is on the dynamics of individual prices, which we simulate with the help of partial-equilibrium models, we also extend our analysis in two directions in order to get an idea about the aggregate implications of our approach. First, we use the models to generate time series for aggregate inflation. This analysis reveals that the PPSI model is slightly more successful in predicting inflation dynamics than the SP model. Second, we illustrate how our partial-equilibrium models of price setting can be integrated into a small-scale DSGE framework. In particular, we show that the PPSI model results in a standard sticky-information Phillips curve, which is equivalent to the one proposed by Mankiw and Reis (2002). The SP model results in a new Keynesian Phillips curve under positive trend inflation (see Ascari and Sbordone (2014), for example). The results for our calibrated small-scale DSGE model indicate that both frameworks are broadly in line with the empirical moments. Nevertheless it is important to identify whether price dynamics are best described by the PPSI model or the SP model because sticky prices and sticky information have different implications for optimal monetary policy. For example, positive trend inflation results in price dispersion and thus is socially costly in sticky-price models but not in sticky-information models.

The remainder of our paper is organized as follows. In Section 2, we review the empirical evidence on price points and present some new evidence for the UK. Section 3 introduces four partial-equilibrium models: our main model (PPSI), the main benchmark (SP), and two additional model variants, which serve to clarify the importance of the main model's two key ingredients, price points and sticky information, for our findings. Analytical expressions for individual price dynamics in log-linearized versions of our models are derived in Section 4. Section 5 describes the main features of our data set. Our simulation strategy is laid out in Section 6 and our main findings about price dynamics are presented in Section 7. Section 8 compares the inflation rates predicted by our models with the one in the data. Section 9 studies the aggregate implications of the four frameworks in general-equilibrium set-ups. Section 10 concludes.

2. Evidence on Price Points

In the last two decades, a rich literature documenting the dynamics of individual prices has emerged. One of the striking regularities observed in the data is the presence of price points, i.e. prices with special endings, for instance the digits 5 or 9, which are used substantially more often than other prices.

Several cognitive and behavioral mechanisms have been proposed as a rationale for price points.[9] One reason for firms to choose threshold prices like \$1.99 may be that consumers perceive the difference between \$1.99 and \$2.00 to be larger than, say, the difference between \$1.98 and \$1.99. Hence demand may drop disproportionately when firms raise their prices from \$1.99 to \$2.00, which makes it comparably likely that they choose \$1.99. A related concept is that of convenient prices, i.e. prices chosen because they require few pieces of money or little change (see Knotek (2008)). This concept helps to explain why certain goods like newspapers are often sold at prices such as \$1.00, \$1.50, or \$2.00. Alternatively, restricting prices to pre-specified sets of prices may be a means of simplifying decision problems for boundedly rational firms or consumers.[10] For the purpose of our paper, it is only important that firms prefer a certain class of prices to other prices; the exact mechanism why these prices are preferred is irrelevant.

Early evidence on the role of price points for price rigidity stems from Kashyap (1995), who analyzes prices in retail catalogues, and Blinder et al. (1998), who conduct a survey on price stickiness among U.S. firms. More recently, Levy et al. (2011) use both scanner and online prices in the U.S. to document that prices with 9-endings occur more frequently than other prices, that they are less likely to change and that the magnitude of price changes is larger for these prices in comparison to prices with non-9-endings.[11]

[9] For surveys see Monroe (1973) and Hamadi and Strudthoff (2016).

[10] It may be noteworthy that simplifying price-setting by choosing only price points would plausibly affect a firm's profits only to a negligible extent.

[11] Price points have been found to be empirically relevant in other countries too. Dhyne et al. (2006) summarize the evidence from the Eurosystem's Inflation Persistence Network and document that in various European countries price points matter for the frequency of price changes.

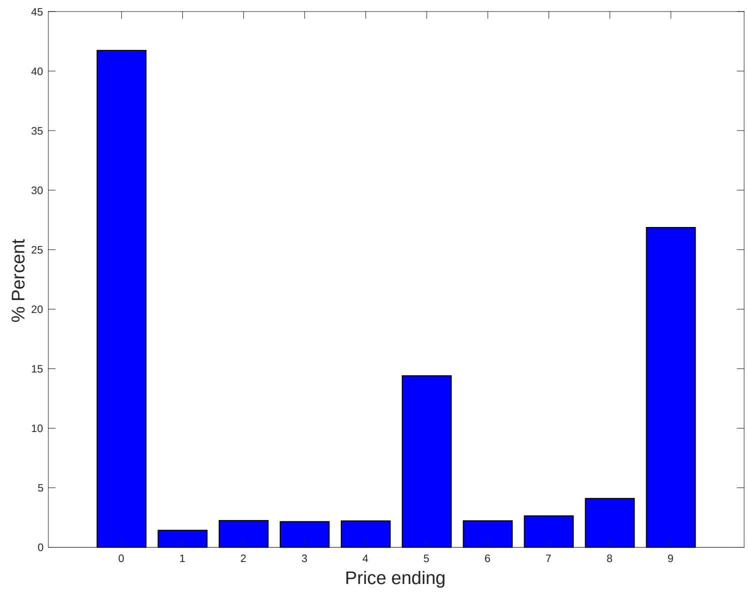

Figure 1: Distribution of final digits for all consumer prices in the UK from February 1996 to December 2016, all prices weighted with the weights used for the construction of the CPI. Source: Office of National Statistics (ONS), own calculations

While the literature on price points has focused on supermarket scanner data and online markets so far, price points are important for a broad set of consumer prices as well. Figure 1, which shows the distribution of last digits of consumer prices in the United Kingdom, demonstrates that the distribution clearly differs from a uniform distribution, which one would plausibly expect if price points played no role.[12] Interestingly, while "9" occurs comparably often as a last digit, the most frequently chosen last digit is "0." This could point to the relevance of convenient prices or the existence of large threshold prices like £49.00, where the last digit before the decimal point is "9." A closer look at the data reveals that for some categories of products in the ONS database, "9" is the most frequent last digit, whereas "0" occurs most often for other product categories.

It may also be instructive to examine the most frequently chosen prices in the ONS database. As can be seen from Table 1, all of the fifteen most frequently used prices end with "99," "00," or "50." It may also be noteworthy that the two largest prices in this list, £10 and £25, appear to be rather special.

[12]The data set is described in more detail in Section 5.

rank	price	freq.	rank	price	freq.	rank	price	freq.
1	1.00	0.92%	6	10.00	0.79%	11	25.00	0.70%
2	2.00	0.84%	7	4.99	0.76%	12	9.99	0.69%
3	0.99	0.82%	8	3.00	0.72%	13	7.99	0.69%
4	1.99	0.81%	9	5.00	0.71%	14	2.50	0.69%
5	3.99	0.79%	10	2.99	0.70%	15	1.50	0.66%

Table 1: Most frequent consumer prices in the UK from February 1996 to December 2016, all prices weighted. Source: ONS, own calculations

3. Model

Having discussed the empirical evidence in favor of price points, we now try to assess their implications for price dynamics. For this purpose, we propose four variants of a textbook model of price setting (see Woodford (2003)) under positive trend inflation and idiosyncratic productivity shocks as in Gertler and Leahy (2008).[13] For the time being, we focus on partial-equilibrium models of price setting. These models will be integrated into a small-scale DSGE set-up in Section 9.

In all four versions of the model, time is discrete and denoted by $t = 0, 1, 2, ...$ The economy is populated by a continuum of monopolistically competitive goods producers, indexed by $j \in [0, 1]$. Each firm j produces the individual good j. The demand for this good is given by

$$Y_{j,t} = \left(\frac{Q_{j,t}}{P_t}\right)^{-\varepsilon} Y_t, \tag{1}$$

where ε ($\varepsilon > 0$) is the elasticity of demand, Y_t aggregate output, $Q_{j,t}$ the price of good j, and P_t is the aggregate price level, which satisfies

$$P_t := \left[\int_0^1 (Q_{j,t})^{1-\varepsilon}\, dj\right]^{\frac{1}{1-\varepsilon}}. \tag{2}$$

[13]For zero trend inflation, our models would entail price-change distributions that would be symmetric around zero. These distributions would be at odds with several empirical findings, e.g. the fact that decreases are typically larger than increases.

Firm j's profits in period t are given by the difference between revenues and total labor costs,

$$\Pi_{j,t} = \frac{Q_{j,t}}{P_t} Y_{j,t} - \frac{W_t}{P_t} N_{j,t}, \tag{3}$$

where W_t is the economy-wide nominal wage, which is taken as given by the firm, and $N_{j,t}$ is the labor input.

The production function is of the form

$$Y_{j,t} = A_t X_{j,t} N_{j,t}^{\gamma}, \tag{4}$$

where $\gamma \in (0, 1]$, A_t is aggregate productivity, which follows a commonly known stochastic process, and $X_{j,t}$ is an idiosyncratic productivity level. For $\gamma < 1$, there are decreasing returns to scale, which could also be interpreted as the production function being of the Cobb-Douglas type but with fixed capital. Firms maximize profits using the stochastic discount factor $\Lambda_{t,t+i} = \beta^i \frac{C_t}{C_{t+i}}$ between periods t and $t + i$, where $\beta \in (0, 1)$ and C_t is aggregate consumption.

In every period, each firm j is hit by a productivity disturbance with probability $1 - \alpha$. When this happens, the firm survives with probability τ. For surviving firms, idiosyncratic productivity changes according to $X_{j,t} = X_{j,t-1} e^{\xi_{j,t}}$, where $\xi_{j,t}$ is an i.i.d. firm-specific shock that is uniformly distributed over the support $\left[-\frac{\chi}{2}, +\frac{\chi}{2}\right]$. If a firm does not survive, which happens with probability $1 - \tau$, conditional on a shock, it is immediately replaced by a new firm with productivity one, i.e. $X_{j,t} = 1$. This can be interpreted as product substitutions. We note that the main purpose of the assumption that firms may die with probability $1-\tau$ is to guarantee a stationary distribution of productivities across firms as in Gertler and Leahy (2008). For our calibration, it will be convenient to introduce $\theta := (1 - \alpha)(1 - \tau)$ as the probability that a given firm exits in a given period.

In our main model (PPSI), firms receive information about all aggregate variables and the realization of the idiosyncratic productivity shock in periods in which they are hit by an idiosyncratic shock. In all other periods, they must act on outdated information.[14] While firms can adjust the prices of their outputs in every period, they must choose these prices subject to a PP restriction, as will be explained in the following.

We assume that each firm j chooses the price for a quantity U_j of the good, where we use $\tilde{Q}_{j,t}$ to denote this price. U_j is constant over time and exogenous for each firm j. Thus the price of quantity U_j, $\tilde{Q}_{j,t}$, and the price per unit of the good, $Q_{j,t}$, are related via $\tilde{Q}_{j,t} = U_j Q_{j,t}$. We can think of the U_j's as different package sizes of the differentiated products.

The PP restriction requires that each firm j choose a log price $\tilde{q}_{j,t} := \ln\left(\tilde{Q}_{j,t}\right)$ that lies in the set $\Delta_j \cdot \mathbb{Z}$, where $\mathbb{Z}$ is the set of positive and negative integers and Δ_j is the exogenously given relative distance between price points. We assume that there are n different values of Δ_j of relative distances between price points with n positive weights ρ_1, ρ_2, ... ρ_n satisfying $\sum_{k=1}^{n} \rho_k = 1$. The set of firms $[0,1]$ can be split into n subsets $[0,\rho_1)$, $[\rho_1, \rho_1 + \rho_2)$, ... $[1-\rho_n, 1]$. Firms in the kth interval all have the same value of Δ_j and can choose log prices $\tilde{q}_t^j$ only from the set $\Delta_j \cdot \mathbb{Z}$. The package sizes u_j are uniformly arranged on $[0, \Delta_j[$ for these firms. Let $q_{j,t}$ be the natural logarithm of the per-unit price $Q_{j,t}$. As $q_{j,t} = \tilde{q}_{j,t} - u_j$ and $\tilde{q}_{j,t} \in \Delta_j \cdot \mathbb{Z}$, the log per-unit price $q_{j,t}$ can only be chosen such that $q_{j,t} \in \Delta_j \cdot \mathbb{Z} - u_j$.

Finally, a few comments on our assumptions regarding price points are in order. First, to motivate the distribution of price points we note that, for \$0.89, the next price point may be \$0.99 but for a price point of \$8.99, the next price point may plausibly be \$9.99.[15] Hence the assumption of constant relative distances between price points appears to be a reasonable approximation. Second, the assumptions that prices refer to fixed quantities U_j of goods and that the U_j's are uniformly arranged have the plausible consequence that the fraction of firms choosing a price point below the price they would charge in the absence

[14]This assumption about when firms receive information updates is closely related to the modeling strategy in Gertler and Leahy (2008), who assume that firms face costs of information acquisition that are too large for firms to search for information in the absence of idiosyncratic shocks but small enough such that firms always acquire information when they are hit by a shock.

[15]This argument is also supported by the evidence presented in Levy et al. (2011). They find that for small prices, prices with 9's in the penny and dime digits are particularly persistent. For more expensive products, they observe more persistence of prices with 9s in the \$1, \$10, and \$100 digits.

of a PP restriction and the fraction of firms choosing a higher price than they would select without a PP restriction are constant over time.[16]

It remains to describe the three additional model variants. The main benchmark with sticky prices (SP) is identical to our main model with the following exceptions: It includes neither sticky information nor a PP restriction but firms can adjust their prices only when they are hit by an idiosyncratic productivity shock. The third model, the PPSP model, features a PP restriction but no information rigidities. Like in the SP model, prices in the PPSP model are sticky in the sense that firms can change their prices only in periods where they are hit by an idiosyncratic shock. In the fourth model, which we label the PP model, firms receive an information update in every period and they can adjust their prices in every period, subject to a PP restriction.[17]

4. Optimal Price-setting

This section derives formal expressions for firms' optimal prices in the four models considered in this paper. We first consider the PPSI and the PP models and analyze the SP and PPSP models afterwards.

To determine the optimal price of firm j in the PPSI and the PP models, it will be useful to introduce $q^*_{j,t}$, the optimal log price that firm j would choose in the absence of sticky information if it could select its price freely in every period, as

$$q^*_{j,t} = \frac{\gamma}{\gamma + \varepsilon(1-\gamma)} \left(-\frac{1}{\gamma} x_{j,t} + \widehat{ulc}_t \right) + p_t, \tag{5}$$

where here and henceforth small letters denote log levels and variables with a "hat" stand for relative deviations from the steady state. In particular, $\widehat{ulc}_t$ denotes the relative deviation of aggregate unit labor costs from their steady-state value. The details of the derivation for (5) and the other equations in this section are given in Appendices A and B.

[16] Otherwise, under positive inflation there would be jumps in the price level in periods where a large fraction of firms adjusted their price upwards to the next price point.

[17] One might also ask about the implications of a fifth model variant with sticky information and no PP restriction. Such a version of model would have the counterfactual implication that all prices change every period.

In the model with price points and no information frictions, the PP model, firm j chooses

$$q_{j,t}^{PP} = \mathcal{T}_j \left\{ q_{j,t}^{*} \right\} = \mathcal{T}_j \left\{ \frac{\gamma}{\gamma + \varepsilon(1-\gamma)} \left(-\frac{1}{\gamma} x_{j,t} + \widehat{ulc}_t \right) + p_t \right\}, \tag{6}$$

where $\mathcal{T}_j : \mathbb{R} \to \mathbb{R}$ is an operator that maps the hypothetical, optimal log price of producer j in the absence of the PP restriction, $q_{j,t}^{*}$, to the closest corresponding log price point $q_{j,t}^{PP} \in \Delta_j \cdot \mathbb{Z} - u_j$. It may be worth stressing that $q_{j,t}^{PP}$ is the log price for one unit of the consumption good. The log price actually chosen by the firm for a package of log size u_j is $\tilde{q}_{j,t}^{PP} = q_{j,t}^{PP} + u_j$.

Analogously, firms in the PPSI model choose the log price point that is closest to the expected log price that would be optimal in the absence of a PP restriction. Formally, a firm j hit by an idiosyncratic shock i periods ago sets the following log price for one unit of its good:

$$q_{j,t}^{PPSI} = \mathcal{T}_j \left\{ \mathbb{E}_{t-i} \left[q_{j,t}^{*\,PP} \right] \right\} = \mathcal{T}_j \left\{ \frac{\gamma}{\gamma + \varepsilon(1-\gamma)} \left(-\frac{1}{\gamma} x_{j,t} + \mathbb{E}_{t-i} \left[\widehat{ulc}_t \right] \right) + \mathbb{E}_{t-i} \left[p_t \right] \right\}, \tag{7}$$

where $\mathbb{E}_{t-i}[\cdot]$ stands for the rational expectations based on all economic variables in period $t-i$ and previous periods. We note that $\mathbb{E}_{t-i}[x_{j,t}] = x_{j,t}$, as the idiosyncratic productivity has remained constant between periods $t-i$ and t.

In the SP model, the price setting equation is given by the standard expression for optimal prices under Calvo pricing and positive trend inflation:

$$q_{j,t}^{SP} = \frac{\gamma}{\gamma + \varepsilon(1-\gamma)} \left(\hat{\psi}_t - \hat{\phi}_t \right) - \frac{1}{\gamma + \varepsilon(1-\gamma)} x_{j,t} + p_t + \ln \left(\frac{\overline{Q}}{\overline{P}} \right), \tag{8}$$

where we use variables with a bar to denote steady-state levels. The auxiliary variables $\hat{\psi}_t$ and $\hat{\phi}_t$ are given by

$$\begin{aligned}
\hat{\psi}_t &= \left(1 - \alpha\beta\bar{\pi}^{\frac{\varepsilon}{\gamma}} \right) \left[\widehat{ulc}_t - \hat{s}_t + \hat{Y}_t - \hat{C}_t \right] + \alpha\beta\bar{\pi}^{\frac{\varepsilon}{\gamma}} \left[\mathbb{E}_t \hat{\psi}_{t+1} + \frac{\varepsilon}{\gamma} \mathbb{E}_t \hat{\pi}_{t+1} \right], &(9) \\
\hat{\phi}_t &= (1 - \alpha\beta\bar{\pi}^{\varepsilon-1})(\hat{Y}_t - \hat{C}_t) + \alpha\beta\bar{\pi}^{\varepsilon-1} \left[\mathbb{E}_t \hat{\phi}_{t+1} + (\varepsilon - 1)\mathbb{E}_t \hat{\pi}_{t+1} \right], &(10)
\end{aligned}$$

where $\overline{\pi}$ is the steady-state level of the gross inflation rate $\pi_t := P_t/P_{t-1}$. The deviation $\hat{s}_t$ of price dispersion from its steady-state value is given by

$$\hat{s}_t = \frac{\varepsilon(\overline{\pi}^{\frac{\varepsilon}{\gamma}} - \overline{\pi}^{\varepsilon-1})}{\gamma(1-\alpha\overline{\pi}^{\varepsilon-1})}\alpha\hat{\pi}_t + \alpha\overline{\pi}^{\frac{\varepsilon}{\gamma}}\hat{s}_{t-1}. \tag{11}$$

Under zero trend inflation, $\hat{s}_t$ would always be zero for a log-linear approximation of the SP model.

Finally, we have to state how prices are selected in the PPSP model. Firm j always chooses the log price that is closest to the log price it would choose under SP price-setting, i.e.

$$q_{j,t}^{PPSP} = \mathcal{T}_j\left\{q_{j,t}^{SP}\right\}. \tag{12}$$

Before proceeding to the main part of the paper where we compare the predictions of our four model variants with the data, we describe the ONS price quote data used for this comparison.

5. ONS Price Quote Data

The CPI micro dataset of the United Kingdom's Office for National Statistics (ONS) is used to compute the official CPI for the UK. The data set starts in January 1996 and is continuously updated. Prices are collected from over 14,000 retail stores and 13 regions across the UK. While the dataset that is available to researchers consists of price data for 556 goods and services on average, ONS uses prices of approximately 700 goods to compute the official CPI. We have verified that the inflation rate constructed only from the price data published by ONS follows the official inflation rate very closely.

We perform several steps to clean the raw data that is available from the ONS website and to generate time series on individual prices. First, we discard prices that are not "valid" according to a flag provided by ONS (and do not enter the official CPI) as well as multiple price quotes for a certain item, shop, and region, as these cannot be used to generate unique time series (this last step eliminates 15.5% of price observations). Following Kryvtsov and Vincent (2017), we split the time series whenever an item substitution occurs. It is well-known that it is crucial to take into account sales in micro price data. We use the sales flag published by ONS to eliminate temporary sales from the data.[18] To generate quarterly data, we use end-of-quarter values. Our final data set contains roughly 7.9 million price observations.

6. Simulation Strategy

The main objective of this paper is to simulate the individual price dynamics implied by the PPSI, SP, PPSP, and PP models in order to assess how well they can explain various findings about price-setting in the UK. In this section, we explain our simulation strategy and the calibration of the models.

We compute the individual price dynamics for the four model variants using the price-setting equations (6)-(8) and (12), respectively. More specifically, we simulate the prices set by 100.000 firms for the time period 1996Q1-2016Q4. While the idiosyncratic shocks are generated by a random number generator in this simulation exercise, we use realized values for the current and past levels of the CPI as well as unit labor costs from ONS. As firms' optimal prices also depend on current and lagged expectations of unit labor costs and the price level, we follow Sbordone (2002) as well as Dupor et al. (2010) and estimate a vector autoregressive model to generate the corresponding forecasts. We use a time horizon (1992Q1-2016Q4) for our VAR model that is longer than the time period of the micro price data, as the PPSI model depends on lagged expectations of current economic variables. The forecasting model includes CPI quarter-on-quarter inflation rates, unit labor costs, and HP-filtered series for real consumption and GDP. The time unit is a quarter, as data on unit labor costs is not available at a higher frequency.

There is a difference between the simulations for the PPSI and PP models on the one hand and the ones for the SP model and the PPSP model on the other hand. As in our simulations firms utilize information about aggregate unit labor costs but do not observe a direct measure of costs on the individual firm level, they rely on a relationship between individual and aggregate costs that involves the measure of price dispersion $\hat{s}_t$.[19] In the PPSI model and

[18] Alternative methods that are used in the literature to identify sales (e.g. by Klenow and Malin (2010)) do not affect our results qualitatively.

[19] The details of the derivations are laid out in Appendices A and B.

the PP model, $\hat{s}_t = 0$ is satisfied in every period t for a log-linear approximation around the steady state, which entails that firms do not have to calculate $\hat{s}_t$ when computing their own costs from aggregate unit labor costs. By contrast, $\hat{s}_t = 0$ does not hold in the SP model and the PPSP model under the assumption of a positive inflation rate in the steady state. Therefore, firms use (11) to compute $\hat{s}_t$ in our simulations. We have confirmed that all our results about individual price dynamics in the SP and the PPSI models are virtually unaffected if we make the assumption that firms (erroneously) use $\hat{s}_t = 0$ in these models as well.

For the calibration, we proceed as follows. We rely on external information to select β, ε, γ, θ, and the different values of Δ_j as well as the corresponding weights ρ_k for $k = 1, ..., n$. Since we use quarterly data, we choose a discount factor of $\beta = 0.99$. In line with Gertler and Leahy (2008), we utilize $\varepsilon = 11$, which implies a steady-state markup of 10% over marginal costs. We set γ to the labor income share of approximately 62%.[20] For the exit probability θ, we select $\theta = 0.10$ because the rate of item substitutions is around 10% in our dataset.

To calibrate the Δ_j's and the corresponding ρ_j's, which are relevant for the PPSI, PP, and PPSP models, we proceed as follows. First, for each shop-item combination separately, we define price points as all posted prices that make up at least 10% of all observations in a window of ±10% around the price.[21] Second, we compute the relative difference when moving upward from one price point to the next one and weight the resulting differences with the relative frequencies of the smaller one of the two price points. Third, we aggregate the resulting distributions of Δ_j using the item-specific and shop-specific weights provided by ONS.

To calibrate the remaining parameters α and χ, the simulated method of moments is used for each model separately.[22] In particular, we simulate the price dynamics for each of the four models and target the frequency and magnitude of price changes in our sample. Table 2 summarizes our calibration. While it is obvious that the SP model can match the

[20] ONS uses different methods to compute the labor share. For our time period, a method developed by ONS itself yields 0.598 and the method developed by the OECD results in 0.635. The value we use is the average of these values.

[21] The price points selected by this procedure represent 83% of all prices.

[22] As the value of θ is independent of the scenario, it is clear from $\theta = (1 - \alpha)(1 - \tau)$ that τ differs across the four scenarios.

frequency of price adjustments for the appropriate value of α, it is less obvious that the PPSI model and the PP model can be equally successful.[23] However, as we will see later, the calibration targets can be attained perfectly in all four models. It may be noteworthy that our calibration implies that parameter α in the PPSI model attains the same value as in Mankiw and Reis (2002).

data				
targeted period	1996Q1 - 2016Q4			
mean magnitude of price changes	10.3%			
frequency of price changes	25.9%			
mean q-o-q inflation	0.49%			
annualized mean inflation	2.0%			
calibrated externally				
β	0.99			
θ	0.10			
ε	11			
γ	0.62			
calibrated internally	PPSI	SP	PPSP	PP
α	0.75	0.67	0.57	0.74
χ	2.64	1.98	1.39	2.43

Table 2: Calibration summary

7. Price Dynamics

We now turn to our simulation results regarding individual price dynamics. These simulations show that our PPSI model can explain several pieces of the evidence on individual price dynamics at least as well as the SP model.

[23] One might be surprised that the frequency of price adjustments is different from $1-\alpha$ in the SP model. This can be understood by noting that we discard all periods where substitutions occur. It is straightforward to see that, conditional on no substitution, the probability of a price change is $1-\alpha/(1-\theta)$.

7.1. Frequency of price adjustment and the magnitude of price changes

Frequency of price adjustment. Table 3 displays our results regarding the frequencies and sizes of price changes for the UK and the four model variants. In the UK, 25.9% of all prices are adjusted in a quarter. We have already noted that all model variants are in line with this moment, which was used as a calibration target.

	UK	PPSI	SP	PPSP	PP
frequency of changes (mean), targeted	0.259	0.259	0.259	0.259	0.259
magnitude of changes (mean), targeted	0.103	0.103	0.103	0.103	0.103
magnitude of changes (median)	0.059	0.075	0.102	0.100	0.085
std. dev. of the magnitude (median)	0.135	0.092	0.061	0.054	0.085
magnitude of increases (mean)	0.096	0.082	0.110	0.108	0.087
magnitude of decreases (mean)	0.118	0.162	0.095	0.098	0.141
changes that are decreases (fraction)	0.309	0.261	0.465	0.449	0.302
mean price change	0.029	0.018	0.014	0.016	0.018
std. dev. of price changes	0.167	0.137	0.119	0.115	0.132
kurtosis of price-change distribution	10.61	4.42	1.83	1.56	3.57
fraction of price changes smaller than 5%	0.437	0.402	0.245	0.144	0.371
fraction of price changes smaller than 2.5%	0.224	0.285	0.122	0.033	0.246
fraction of price changes smaller than 1%	0.060	0.181	0.049	0.005	0.113
probability of revisiting a price	0.15	0.15	0.00	0.24	0.17
average number of unique prices	2.94	2.83	3.33	2.74	2.74

Table 3: Frequency and size of price changes as well measures of back-and-forth movements.

Magnitude of price changes. The empirical evidence that prices change by much more than necessary to catch up with inflation has been emphasized since Bils and Klenow (2004). As argued by Golosov and Lucas (2007), a model has to involve idiosyncratic shocks in order to be able to explain this pattern. Because all model variants include such shocks, we are able to hit the calibration target of an average magnitude of price changes of 10.3% in all cases. Somewhat interestingly, in the data, the median magnitude of price changes is considerably smaller compared to the mean. The PPSI is quite successful in replicating this pattern, as opposed to the SP model.

How can this relative success of the PPSI model be explained? In the PPSI model, there are two reasons for price changes. First, a productivity shock may materialize, which typically requires a large downward or upward adjustment due to the comparably large variance of these shocks. Second, firms adjust prices when they anticipate a change in the price level that makes an adjustment by Δ_j worthwhile. In general, these changes are small and positive. As a consequence, for price decreases, the mean and the median are similar but, for price increases, the median lies below the mean.[24] Overall, the median magnitude of price changes is smaller than its mean.

By contrast, in the SP model prices only change in the presence of idiosyncratic shocks, which are drawn from a uniform distribution. Thus both price increases and price decreases are approximately uniformly distributed. As a result, the median magnitude of price changes is almost identical to the respective mean.

Midrigan (2011) stresses that it is important for models of price setting to be in line with the dispersed distribution of price changes in micro data. A comparison of the standard deviations of the magnitude of price changes in Table 3 demonstrates that the PPSI model is more successful than the SP model in this respect. This can be understood by noticing that both models are calibrated to the same mean magnitude of price changes, but that the PPSI model implies more small price changes than the SP model.

Finally, a few words on the other two models may be in order. The PPSP model behaves very similarly to the SP model. This is due to the fact that, like in the SP model, price changes in the PPSP model take place only when firms are hit by an idiosyncratic shock.[25] The PP model is similar to the PPSI model in that there are two sources of price changes: changes due to idiosyncratic shocks and changes to catch up with movements in the price level. Qualitatively, the PP model therefore produces results that are similar to the ones for the PPSI model.

[24] In the PPSI model, the ratio between the median and the mean magnitude of price increases (decreases) is 0.55 (1.02). In the data, the respective values are 0.55 and 0.68. In the SP model, both values are approximately one.

[25] More precisely, an idiosyncratic shock does not always cause a price change in the PPSP model, as the desired price change may be too small compared to the smallest admissible price change Δ_j.

Magnitude of price changes for increases vs. decreases. It is a puzzling asymmetry in empirical data that the magnitude of price decreases tends to be larger than the size of price increases. Burstein and Hellwig (2007) document this fact for the Dominick's database and KK provide evidence that for regular prices in the BLS data set, increases average 10.6% whereas decreases average 13.3%.

Our findings for the UK are in line with these previous findings with mean price increases of 9.6% and decreases of 11.8%. Table 3 shows that the PPSI model generates average increases of 8.2% and average decreases of 16.2% and is thus able to replicate this pattern qualitatively. This is a consequence of our earlier observation that the PPSI model produces many small price increases.

In the SP model, price increases are larger than decreases on average because, every time a firm is allowed to adjust its price, the new price is determined by two main factors: the size of the idiosyncratic productivity shock, which has zero expected mean, and changes in the expected future price levels since the last adjustment, which are usually positive under a positive trend inflation rate.

Distribution of price changes. Table 3 reports the means and standard deviations of the distributions of price changes for our different models. Both the PPSI and the SP model make reasonable predictions, while the PPSI model's predictions are somewhat closer to the values found in the data. With respect to the kurtosis of the distribution of price changes, all models produce lower values than those found in the data but the PPSI model comes closest to the empirical moment.[26,27]

KK emphasize that, despite the large mean magnitude of price changes, small price changes are rather frequent. They report that roughly 40% of all price changes are smaller

[26] Alvarez et al. (2016) show that empirical measures of kurtosis are upward-biased if heterogeneity is not taken into account. Hence we follow their suggestion and de-mean all price changes at a cell level and divide all price changes by the standard deviation for the respective cell, where a cell is a particular pair of shop type and item. For the models with a PP restriction, we use an analogous procedure, where a cell is a set of firms with a particular value of Δ_j.

[27] Alvarez et al. (2016) find that the kurtosis is in the vicinity of four in low-inflation countries. We have verified that the larger value that we find does not change qualitatively if we eliminate price changes smaller than 1% or if we consider monthly rather than quarterly data. For the alternative measure of kurtosis used by Petrella et al. (2018), we obtain 1.9, which appears to be broadly in line with Petrella et al.'s findings.

than 5%. Table 3 shows a similar value for the UK.[28] While the PPSI is successful in replicating the fractions of price changes that are smaller than 5% or 2.5%, it produces too many price changes that are smaller than 1%. One might speculate that the inclusion of small menu costs would improve the performance of the PPSI model in this regard. The SP model tends to produce too few small price changes. This is a consequence of the observations that price changes in the SP model occur only if there is an idiosyncratic shock and that idiosyncratic shocks are typically large.

KK find that 43.4% of all price changes are price decreases. We find a somewhat smaller value of 30.9% for the UK and our sample period.[29] The PPSI model, which produces many small price changes, comes closer to this value than the SP model, where price increases and decreases are roughly equally likely.

Revisiting prices. Data on individual prices indicate that prices move back and forth between a few rigid values (NS, Eichenbaum et al. (2011), Knotek (2016)). This pattern can also be found for the UK sample under consideration. In particular, we compute the frequency with which, conditional on a price change in a particular period, the new price was chosen in one of the preceding 7 quarters. Table 3 shows that this probability of revisiting an old price amounts to 15% in the data.[30] Clearly, the assumption that prices can only be chosen from a discrete set of price points potentially enables the PPSI model to generate non-negligible probabilities of revisiting prices, in contrast with the SP model, where prices can be any real number. In fact, the PPSI model reproduces the value in the data, whereas the probability of revisiting an old price is zero in the SP model.

Table 3 also reports the average number of unique prices that is chosen in intervals of a length of 8 quarters.[31] Although the probability of revisiting a particular price is zero in the SP model, the number of unique prices is similar to the one in the data because prices change only occasionally. In the PPSI model, prices adjust infrequently and, if they adjust,

[28]Eichenbaum et al. (2014) identify several factors that may lead to spurious small price changes in micro price data. These factors appear to be less relevant for our data set.

[29]Using the appropriate weights, we compute the fraction of price changes that are decreases for each quarter and then compute the average of these quarterly values.

[30]The same measure is used in Ilut et al. (2016) for a different time horizon and monthly data. It is also closely related to the frequency of "comeback prices" computed in Klenow and Malin (2010).

[31]Ilut et al. (2016) compute a related measure of "novel prices."

there is a non-negligible probability of an old price being chosen. Both factors jointly lead to a number of unique prices that comes close to the value we find in the data.

7.2. Frequency and magnitude of price changes as functions of the age of the price

Hazard rates. Simple state-dependent pricing models like menu-cost models typically predict an increasing hazard curve, i.e. an increasing probability of a price change as a function of the duration of a price spell.[32] As shown by KK, NS, and Klenow and Malin (2010), this implication is not supported by the data.

Estimating the shape of hazard functions is empirically challenging because of substantial heterogeneity in the frequency of price adjustment across goods. Here we follow the approach used by KK, who first sort all items into deciles according to the frequency of price changes, then compute the hazard functions for all deciles separately, divide them by the unconditional frequency of a price change for the respective decile and finally calculate the average of the resulting hazard functions.

The left-hand side of Figure 2 shows the hazard functions for the UK sample and the four model variants, where we take into account heterogeneity in the way described above. It is instructive to examine the empirical hazard function first. In line with previous results in the literature, the hazard function has spikes after 4, 8, and 12 quarters. Regressing the probability of a price change on the age of a price with dummies for 4, 8, and 12 quarters reveals a slightly positive slope of the hazard function of 0.029. This has the interpretation that an increase of a price's age by one year leads to an increase of the probability of a price change by approximately 12%.

To illustrate the workings of our main model, the second row shows the hazard function for the subset of firms in our PPSI model that are characterized by a value of $\Delta_j = 5\%$. While the hazard curve is slightly upward sloping initially, it features a significant peak around the tenth quarter. The reason is straightforward. In the PPSI model, there are two main causes of price changes: idiosyncratic shocks and expected changes in the price level. The first mechanism alone would produce a flat hazard curve. The second factor requires an adjustment of the price level from time to time due to the positive level of trend inflation. As

[32] NS highlight that the hazard function can take many different forms in models with idiosyncratic shocks.

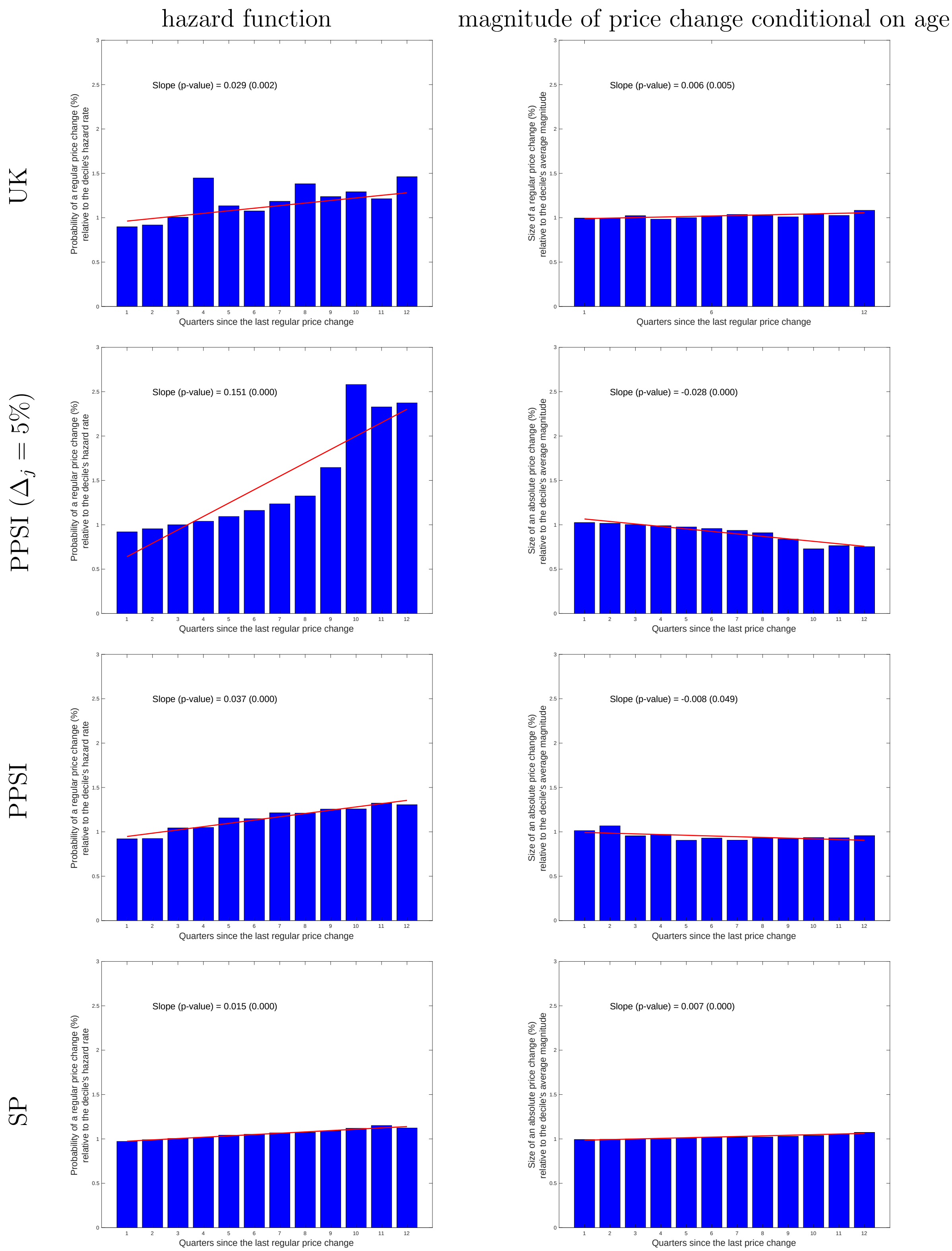

Figure 2: Hazard rates and the magnitudes of price adjustment conditional on age. In the regression for the slope coefficient that utilizes UK data, we include a dummy for year fixed effects.

the average quarter-on-quarter inflation rate is 0.49% for our period sample and the relative difference between price points is $\Delta_j = 5\%$ for the firms under consideration, one would expect that firms are comparably likely to adjust their prices after $5/0.49 \approx 10$ quarters, which is exactly what Figure 2 shows.

The panel located in the first column and the third row shows the hazard functions for the entire set of firms in the PPSI model. Because the distribution of Δ_j's involves many different values, the peak that arises for $\Delta_j = 5\%$ disappears. The hazard rate has a positive slope, which is slightly larger than the one in the data.

The first panel in the bottom row shows that the hazard function for the SP model has a positive slope as well, which is surprising given that the hazard curve is flat by construction under Calvo pricing. The positive slope is an artifact of the procedure that we employ to take into account heterogeneity. Thus this panel confirms that it is not obvious how heterogeneity should be taken into account and that the exact values for the slopes should be taken with a pinch of salt. With this caveat in mind, we would argue that both the PPSI and SP model are roughly in line with the slope of the hazard curve found in the data.

Magnitude of price changes as a function of age. Another important empirical finding in the literature is that the mean magnitude of relative price changes is approximately independent of the time since the last adjustment (KK, Klenow and Malin (2010)). Our empirical analysis broadly confirms this pattern, as can be seen from the second panel in the first row of Figure 2. The slope of the magnitude of price changes as a function of the price's age is quite low and around 0.006. Roughly speaking, this value has the interpretation that, for each quarter that the price is not adjusted, the magnitude of the next price adjustment increases by 0.6%.

The typical prediction of time-dependent pricing models is that prices are adjusted more strongly if they have not been adjusted for a longer time period.[33] Although our SP model falls into the class of time-dependent pricing models, it is quite successful in replicating the empirical finding under consideration, as can be seen from the second panel in the bottom row. The success of the SP model is due to the fact that our calibration selects a comparably

[33]This prediction can be understood by noting that the optimal price drifts away from the current price as time passes and therefore larger adjustments are necessary for prices that have not been adjusted for a long time.

large variance of idiosyncratic shocks. Hence the size of price changes is mostly driven by the realization of the idiosyncratic shock and hardly influenced by the comparably modest changes in the price level that occurred since the price was last adjusted.

The PPSI model implies a trough at around 10 quarters for firms with $\Delta_j = 5\%$ (see the second panel in the second row). The intuition is straightforward. As we have explained before, positive trend inflation causes firms in the PPSI model to adjust prices upwards by Δ_j from time to time even in the absence of idiosyncratic shocks. For firms with $\Delta_j = 5\%$, this occurs after approximately 10 quarters.[34]

For all firms taken together in the PPSI model, the trough at 10 quarters disappears and the resulting function has a slightly negative slope, in contrast with the slightly positive slope found in the data. While it is important to remember that the procedure that controls for heterogeneity can introduce small biases, the SP model produces a slope of the hazard function that is somewhat closer to the slope found for our UK sample.

7.3. Price changes and inflation

Relationships of the frequency and size of price adjustment with inflation. KK find that the frequency of price changes, which we denote as fr_t, co-moves with inflation π_t. For the UK, estimating

$$fr_t = \beta_\pi \pi_t + b + \epsilon_t \tag{13}$$

with error term ϵ_t and intercept b via OLS produces a significant positive coefficient $\beta_\pi = 2.52$ (see Table 4). Thus a quarter-on-quarter inflation rate that is higher by 1 percentage point is associated with a frequency of price adjustment that is higher by 2.5 percentage points.[35] This pattern is strong evidence against time-dependent pricing in general and the SP model in particular.

Table 4 also confirms that the respective coefficient is not significantly different from zero in our simulations of the SP model. By contrast, the PPSI model results in a coefficient of 1.4, which is smaller than in the data but has the correct sign. Intuitively, larger levels of

[34] It is noteworthy that, at the trough of the graph for the PPSI model, prices change by more than $\Delta_j = 5\%$ on average because some changes are induced by idiosyncratic shocks, which materialize with a 25% probability every period and have sizable variance.

[35] KK find a coefficient of 2.38 for monthly data.

inflation require more firms to adjust their prices in the absence of idiosyncratic productivity shocks.

	UK	PPSI	SP	PPSP	PP
fr_t	2.52 (0.02)	1.40 (0.00)	0.03 (0.46)	0.05 (0.20)	10.12 (0.00)
dp_t	1.48 (0.00)	0.71 (0.00)	0.70 (0.00)	0.93 (0.00)	2.05 (0.00)
fr_t^+	3.87 (0.00)	1.68 (0.00)	0.48 (0.00)	0.83 (0.00)	12.37 (0.00)
dp_t^+	-0.29 (0.44)	-0.02 (0.82)	0.35 (0.00)	0.31 (0.00)	-4.04 (0.00)
fr_t^-	-1.35 (0.00)	-0.28 (0.00)	-0.45 (0.00)	-0.78 (0.00)	-2.25 (0.00)
dp_t^-	-0.31 (0.55)	-0.43 (0.00)	-0.33 (0.00)	-0.28 (0.00)	1.15 (0.00)
$fr_t^{\leq 10\%}$	1.99 (0.05)	1.24 (0.00)	0.01 (0.77)	-0.08 (0.01)	9.0 (0.00)
$fr_t^{>10\%}$	0.53 (0.09)	0.16 (0.00)	0.02 (0.53)	0.14 (0.00)	1.14 (0.00)

Table 4: Coefficients for regressions of different variables on π_t and a constant. p-values in parentheses. fr_t = the fraction of items with changing prices, dp_t = the average relative price change, fr^+ = fraction of items with rising prices, dp^+ = magnitude of price increases, fr^- = fraction of items with falling prices, dp^- = magnitude of price decreases.

It is noteworthy that the PP model involves a much more sizable coefficient of 10.12. This is plausible, as all firms in the PP model observe unusual rates of inflation immediately, in contrast with the PPSI model, where the exact level of inflation is observed only in periods where firms are hit by idiosyncratic shocks. Again, the results for the PPSP model are similar to those for the SP model. In the PPSP model, the frequency of price adjustments does not co-move with inflation as prices can be adjusted only when idiosyncratic shocks arrive, which happens with a constant probability.

In line with KK, we find a positive association between inflation π_t and the mean price change dp_t in our data set. A regression analogous to (13) leads to positive coefficients for both the PPSI and the SP model, where the coefficients are smaller than for the data in both cases. Again it may be instructive to look at the PP model as well. Because all firms constantly observe all aggregate variables and inflation in particular, the mean price change fluctuates more strongly with the inflation rate than in the PPSI model.

Relationships of the frequencies of price increases and price decreases with inflation. NS and, more recently, Nakamura et al. (2018) have documented that the frequency of price increases, which we denote as fr_t^+, changes substantially over time and co-varies with inflation. By comparison, the frequency of price decreases, fr_t^-, is more stable. Table 4 suggests a similar pattern for the UK. Regressing fr_t^+ on inflation produces a positive coefficient, which has a larger magnitude than the negative coefficient that obtains when fr_t^- is the dependent variable.

Table 4 also shows that this pattern can be reproduced qualitatively by the PPSI model but not by the SP model. In the PPSI model, the current inflation rate affects the frequency of the small positive adjustments that are caused by expected increases in the price level. In periods of high inflation, there are more of these small increases and thus the overall frequency of price increases is higher. By comparison, the frequency of price decreases is affected only to a smaller extent by higher inflation rates, as most price decreases are triggered by negative idiosyncratic shocks. In the SP model, the frequency of price changes is obviously constant but more price changes correspond to increases when inflation is high. As $fr_t^+ + fr_t^- = fr_t$, the regression coefficient for fr_t^+ has the opposite sign but identical magnitude compared to the coefficient for fr_t^-.

Finally, it may be instructive to examine the coefficients obtained for the PPSP and the PP model. We notice again that the PPSP model generates results that are qualitatively similar to those implied by the SP model. As prices are only adjusted in response to idiosyncratic shocks in the PPSP model, the magnitudes of the coefficients for fr_t^+ and fr_t^- are not statistically significantly different from one another. Like the PPSI model, the PP model involves that the frequency of price increases co-moves more strongly with inflation than the frequency of price decreases. This pattern is more pronounced compared to the PPSI model because, in the PP model, all firms become immediately aware of changes in inflation.

Relationship of the frequencies of small and large price changes with inflation. Our discussions of the PPSI model and the PP model have revealed that large price changes are different from small price changes in these models. Large price changes are triggered by idiosyncratic shocks, which arrive with constant probability. By contrast, small price changes are usually caused by changes in the price level. Hence it may be interesting to examine whether there is empirical evidence in favor of this difference between small and large price changes.

The last two rows of Table 4 show the coefficients for regressions of the form (13), where the dependent variable is $fr_t^{\leq 10\%}$, the frequency of price changes that are at most 10%, or

$fr_t^{>10\%}$, which is the frequency of price changes that are strictly larger than 10%. These results illustrate that both in the PPSI model and in the data the frequency of small price changes co-moves more strongly with inflation than the frequency of large price changes. The same pattern can be found for the PP model in a particularly pronounced way. The SP model, however, is at odds with the empirical evidence.[36] To sum up, the empirical relationship between the frequencies of small and large price changes with inflation provides support for the main mechanism inherent in the PPSI model.

Discussion. At this point, it is useful to discuss a general pattern that has emerged in the preceding analysis. As shown in Table 4, both the PPSI model and the PP model are compatible with several empirical patterns regarding the relationship of inflation and price setting qualitatively. At the same time, the magnitude of the effects is often underestimated by the PPSI model but overestimated by the PP model. This suggests that information rigidities may be too strong in the PPSI model and too weak in the PP model. As a consequence, it might be interesting to consider an intermediate case, where information is updated not only in periods where firms are hit by idiosyncratic shocks but where information about the aggregate state of the economy arrives with positive probability in other periods as well.

7.4. Inflation variance: intensive vs. extensive margin

A major purpose of studying price dynamics is to understand what drives fluctuations in inflation: Is it that the frequency of price changes varies or that firms change prices by different amounts? Put differently, are inflation dynamics driven by the extensive margin (EM) or the intensive margin (IM)?

To explore these questions, KK use a decomposition of the inflation variance into terms capturing the intensive margin and terms capturing the extensive margin. More specifically,

[36] Somewhat surprisingly, the PPSP model predicts a decrease of the frequency of small price changes when inflation is large. This can be explained by observing that some price changes that would be close to but smaller than 10% without a PP restriction may lead to a price change larger than 10% in the presence of a PP restriction.

the decomposition is given by[37]

$$var(\pi_t) = \underbrace{var(dp_t)\overline{fr}^2}_{\text{IM term}} + \underbrace{var(fr_t)\overline{dp}^2 + 2\,\overline{fr}\,\overline{dp}\,cov(fr_t, dp_t) + \mathcal{O}_t}_{\text{EM terms}}, \tag{14}$$

where dp_t is the average relative price change and the values with a bar correspond to time averages. $\mathcal{O}_t$ are higher-order terms that are functions of fr_t.

The results from this variance decomposition for our dataset and the different models are displayed in Table 5. We obtain, like KK, that the intensive margin is more important for the variance of inflation than the extensive margin. Compared to KK, we find that a larger share of the inflation variance can be attributed to the extensive margin (36% compared to 9% in KK). Obviously, the SP model assigns all fluctuations in the inflation rate to the intensive margin because the frequency of price adjustments is fixed by assumption. The PPSI model also attributes positive weight to the extensive margin. The extensive margin is even more important in the PP model.

	UK	PPSI	SP	PPSP	PP
IM (in percent)	64	76	100	99	62
EX (in percent)	36	24	0	1	38
POS (in percent)	82	66	55	55	82
NEG (in percent)	18	34	45	45	18

Table 5: Variance decomposition: extensive margin vs. intensive margin and POS vs. NEG.

For completeness, we also consider another decomposition proposed by KK, which addresses the question whether fluctuations in inflation are the consequences of changes in price increases or price decreases. KK note that inflation can be written as

$$\pi_t - 1 = fr_t^+ dp_t^+ - fr_t^- dp_t^-, \tag{15}$$

[37]See KK for a derivation.

where dp_t^+ and dp_t^- denote the average magnitudes of increases and decreases.[38] With the help of (15), the variance of inflation can be expressed in the following way

$$
\begin{aligned}
var(\pi_t) = & \underbrace{var(fr_t^+ dp_t^+) - cov(fr_t^+ dp_t^+, fr_t^- dp_t^-)}_{\text{POS term}} \\
& \qquad + \underbrace{var(fr_t^- dp_t^-) - cov(fr_t^+ dp_t^+, fr_t^- dp_t^-)}_{\text{NEG term}}.
\end{aligned}
\tag{16}
$$

As shown in Table 5, the variance of inflation is dominated by changes in price increases. In this regard, the PPSI slightly outperforms the SP model.

7.5. Discussion

Drawing on data for the UK, the preceding analysis has revisited many stylized facts that have been discovered by other authors for other data sets. As the PPSI model comes closer to the empirical findings than the SP model in many but not all cases, one might ask which features of the data are most important for a model of price setting to match. We would argue that these are the moments that allow for a clear-cut distinction between fundamentally different approaches to modeling price dynamics: (i) time-dependent pricing like the Calvo approach, (ii) menu-cost models, and (iii) our approach involving price points and sticky information. Distinguishing between these approaches is important as they have different implications for the welfare consequences of long-term inflation. As has been highlighted by Nakamura et al. (2018), Calvo pricing leads to larger costs of inflation than the approach based on menu costs. In our PPSI model, high trend inflation involves no costs at all.[39]

We would therefore argue that the empirical finding that the frequency of price adjustment co-varies with inflation is important for a model to match. The PPSI model is successful in this regard, while the SP model is not. As argued by Knotek (2016), a prediction that is specific to models with an important role for price points is that prices return to previous

[38] Recall that π_t is the gross rate of inflation, i.e. $\pi_t = P_t/P_{t-1}$. Thus $\pi_t - 1$ is the net rate.

[39] Obviously, there may be additional costs of inflation that are ignored by our approach. One plausible extension of our model would involve a mechanism that links higher levels of inflation to a higher volatility of inflation, which tends to be socially wasteful under sticky information.

values with a non-negligible probability. It therefore may be noteworthy that the empirical frequency with which prices are revisited lends support to the PPSI model.[40,41]

8. Inflation Dynamics

As a next step, we examine how well the different models predict the evolution of inflation. For this purpose, we compute the inflation rates from the individual prices predicted by the four models and compare them to the inflation rate in the data.[42] Figure 3 displays 4-quarter moving averages and shows that all four models make reasonable predictions regarding inflation. In particular, the root-mean-squared errors (RMSE) are of similar magnitudes in all cases.

9. Small-scale DSGE model

In this section, we integrate the four partial-equilibrium models considered so far into a small-scale DSGE framework. The purpose of this exercise is twofold. First, we demonstrate that the models entail different Phillips curves. Second, we show in calibrated versions of our models that the general-equilibrium version of the PPSI model is at least as successful in explaining aggregate moments as the SP model.[43]

---

[40] Complex models with multiple menu costs (Eichenbaum et al. (2011), Kehoe and Midrigan (2015)) are also in line with the observation that previously chosen prices may be revisited comparably often. However, these approaches cannot explain why certain prices, e.g. those with 9-endings, are chosen more frequently than others.

[41] A more detailed discussion of the relationship between our approach and menu-cost models can be found in Appendix C.

[42] As has been highlighted in Section 5, a comparably small share of prices is not contained in the price quote data set that is publicly available. Hence, for our comparisons, we construct an inflation rate that takes into account only the goods for which micro price data is available.

[43] Some authors find that sticky-price models are superior to sticky-information models, provided that backward-looking agents are included (see e.g. Kiley (2007) and Trabandt (2007)). However, the introduction of backward-looking agents does not have strong microfoundations. Klenow and Willis (2007) find that firms' price decisions depend on outdated information about aggregate shocks, which supports the idea that sticky information is important for understanding inflation dynamics. More recent contributions to this literature include Dupor et al. (2010), Kaufmann and Lein (2013), Kiley (2016), and Eggertsson and Garga (2017).

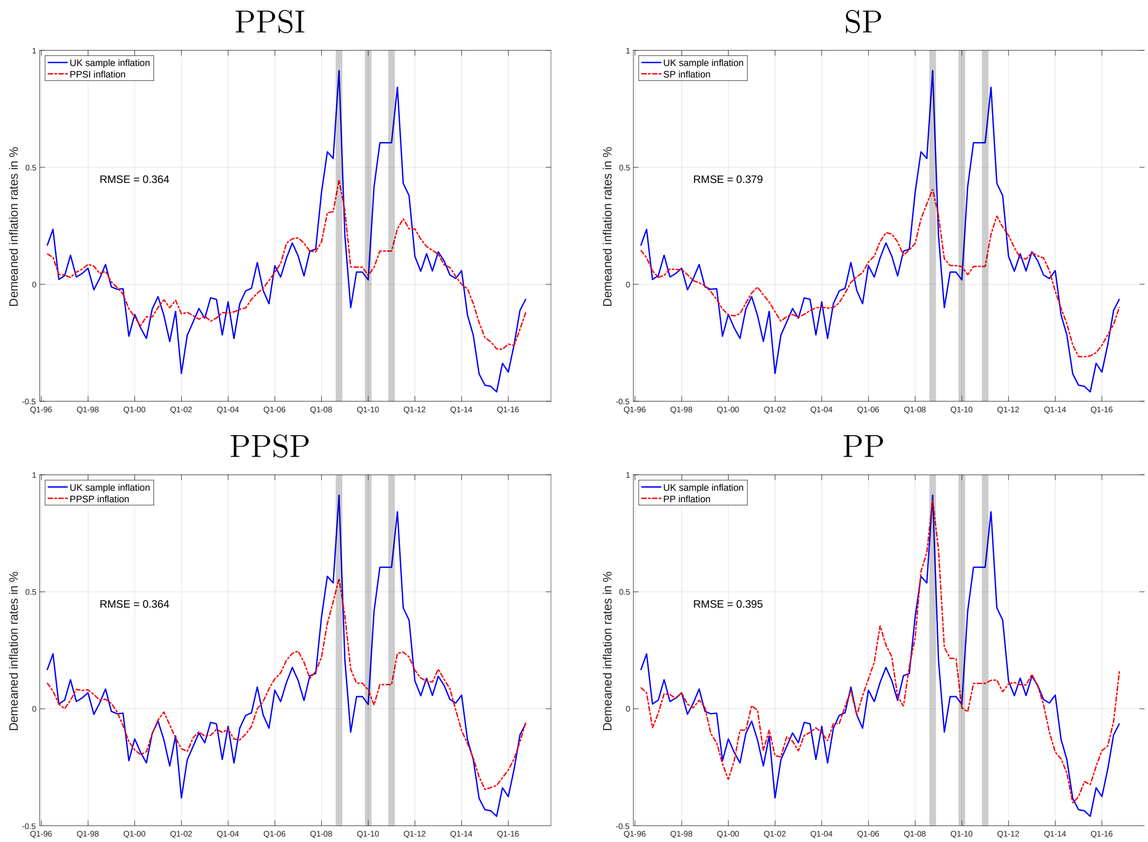

Figure 3: Inflation dynamics predicted by the different models vs. inflation in the data. The figure shows four-quarter moving averages. No averaging procedure applied when the root mean squared errors (RMSE) are computed. Quarters with VAT changes have been discarded.

9.1. Set-up

In the following, we describe the additional assumptions that are necessary for extending the four models to general-equilibrium settings. For the firm sector, it remains to specify the process for aggregate productivity. The log deviation $\hat{A}_t$ of aggregate productivity from its steady-state level $\overline{A}$ is given by

$$\hat{A}_t = \rho_A \hat{A}_{t-1} + \epsilon_t^A, \tag{17}$$

where $0 < \rho_A < 1$ and the ϵ_t^A's are independent, normally distributed disturbances with mean zero and variance σ_A^2.

There is a continuum of households that own identical shares of all firms and receive firms' profits as dividends. The households' instantaneous utility function in period t is

$$u(C_t, N_t) = \ln(C_t) - \frac{N_t^{1+\varphi}}{1+\varphi}, \tag{18}$$

where φ is a positive parameter, N_t stands for the household's supply of labor and C_t is a consumption basket. C_t is given by a Dixit-Stiglitz aggregator function

$$C_t = \left[\int_0^1 (C_{j,t})^{\frac{\varepsilon-1}{\varepsilon}} dj \right]^{\frac{\varepsilon}{\varepsilon-1}}, \tag{19}$$

where $C_{j,t}$ denotes the quantity of good $j \in [0,1]$ consumed in period t. Here ε has the interpretation as the elasticity of substitution between the differentiated goods.

Utility in future periods is discounted by the factor $\beta \in (0,1)$. In each period t, the real flow budget constraint is

$$\int_0^1 \frac{Q_{j,t}}{P_t} C_{j,t} dj + \frac{\frac{1}{1+i_t} B_t - B_{t-1}}{P_t} = \frac{W_t}{P_t} N_t + T_t, \tag{20}$$

where B_t denotes bond holdings, i_t the nominal interest rate, and T_t a real transfer, which includes the profits of firms, the government's seigniorage revenues, and the funds that are required to finance government expenditures. Bonds are in zero net supply.

We assume that monetary policy can be described by a Taylor rule of the form:

$$i_t = \rho_i i_{t-1} + a_\pi \hat{\pi}_t + a_y \hat{Y}_t + (1-\rho_i)\bar{i} + \mu_t, \tag{21}$$

where $\hat{\pi}_t$ is the log deviation of the inflation rate from its long-run gross value $\overline{\pi}$ and $\hat{Y}_t$ is the log deviation of output from its steady state level. $\rho_i \in (0,1)$, a_π, and a_y are constants. The long-run nominal interest rate satisfies $1 + \bar{i} = \frac{\overline{\pi}}{\beta}$. μ_t stands for monetary policy shocks, which are independent and normally distributed with mean zero and variance σ_μ^2.

Government expenditures $G_t = \left[\int_0^1 (G_{j,t})^{\frac{\varepsilon-1}{\varepsilon}} dj \right]^{\frac{\varepsilon}{\varepsilon-1}}$ are pure waste, where $G_{j,t}$ denotes the quantity of good $j \in [0,1]$ consumed by the government in period t. The government's demand for individual good j is $G_{j,t} = \left(\frac{Q_{j,t}}{P_t}\right)^{-\varepsilon} G_t$. The log deviation $\hat{G}_t$ of government expenditures from its long-run level, $\overline{G}$, is given by an AR(1) process:

$$\hat{G}_t = \rho_G \hat{G}_{t-1} + \epsilon_t^G,$$

where $0 < \rho_G < 1$ and the ϵ_t^G's are independent, normally distributed disturbances with mean zero and variance σ_G^2. The government levies lump-sum taxes to balance its budget in every period.

9.2. Equilibria

As a next step, we describe the conditions that determine the equilibria of the log-linearized small-scale DSGE model. The household's utility maximization problem results in standard conditions, which can be log-linearized to[44]

$$\begin{aligned} w_t - p_t - \ln\left(\frac{\overline{W}}{P}\right) &= \varphi \hat{N}_t + \hat{C}_t, && (22) \\ \hat{C}_t &= -\left(i_t - \mathbb{E}_t\left[\hat{\pi}_{t+1}\right] - \bar{i}\right) + \mathbb{E}_t\left[\hat{C}_{t+1}\right]. && (23) \end{aligned}$$

Unit labor costs are determined by the following equation:

$$\widehat{ulc}_t = w_t - p_t - \ln\left(\frac{\overline{W}}{P}\right) + \hat{N}_t - \hat{Y}_t. \tag{24}$$

The aggregate production function is

$$\hat{Y}_t = \hat{A}_t - \hat{s}_t + \gamma \hat{N}_t. \tag{25}$$

The goods-market clearing condition, $Y_t = C_t + G_t$, yields the following log-linearized relationship:

$$\hat{Y}_t = \frac{\overline{Y} - \overline{G}}{\overline{Y}} \hat{C}_t + \frac{\overline{G}}{\overline{Y}} \hat{G}_t. \tag{26}$$

[44] Minimizing costs for a given size of the consumption basket C_t yields the demand specified in (1).

The four models lead to different Phillips curves (for details of the derivations see Appendices A and B). The PP model is equivalent to a flex-price model. Hence $\widehat{ulc}_t = 0$ and $\hat{s}_t = 0$ hold in all periods. The PPSI model results in a standard sticky-information Phillips curve

$$\begin{aligned}\hat{\pi}_t =& \frac{\gamma}{\gamma + \varepsilon(1-\gamma)} \frac{1-\alpha^{PPSI}}{\alpha^{PPSI}} \widehat{ulc}_t \\ &+ (1-\alpha^{PPSI}) \sum_{i=0}^{\infty} \left(\alpha^{PPSI}\right)^i \mathbb{E}_{t-1-i}\left[\hat{\pi}_t + \frac{\gamma}{\gamma+\varepsilon(1-\gamma)}\left(\widehat{ulc}_t - \widehat{ulc}_{t-1}\right)\right],\end{aligned}$$

where the log deviations of unit labor costs from their steady state value are given by (24) for $\hat{s}_t = 0$.

For the SP model, we obtain the standard new Keynesian Phillips curve

$$\hat{\pi}_t = \frac{1-\alpha^{SP}\overline{\pi}^{\varepsilon-1}}{\alpha^{SP}\overline{\pi}^{\varepsilon-1}} \frac{\gamma}{\gamma+\varepsilon(1-\gamma)}\left(\hat{\psi}_t - \hat{\phi}_t\right), \tag{27}$$

where $\hat{\psi}_t$ and $\hat{\phi}_t$ are given by (9) and (10). The PPSP model leads to the same Phillips curve like the SP model. The only difference is that parameter α^{SP} has to be replaced by α^{PPSP}.

The equilibria of the four model variants are given by paths of $\hat{Y}_t$, $\hat{C}_t$, $\hat{N}_t$, $\widehat{ulc}_t$, $w_t - p_t$, $\hat{\pi}_t$, i_t and $\hat{s}_t$ for exogenous shock processes $\hat{G}_t$, $\hat{A}_t$, and μ_t such that equations (21)-(26) and the respective Phillips curve and the corresponding equation for $\hat{s}_t$, i.e. $\hat{s}_t = 0$ or (11), hold.

9.3. Aggregate Dynamics

To compare the four macroeconomic models in this paper, we need to pin down a few remaining parameters, which were not relevant for the simulations in Section 7. We use the standard value of $\varphi = 1$ for the inverse of the Frisch elasticity of labor demand. For the rest of the parameters, we rely on Harrison and Oomen (2010) and set $a_\pi = 0.24$, $a_y = 0.21$, $\rho_i = 0.87$, $\frac{\overline{G}}{\overline{Y}} = 0.19$, $\rho_G = 0.96$, $\rho_A = 0.89$, $\sigma_\mu = 0.0007$, $\sigma_G = 0.008$, and $\sigma_A = 0.006$.

Table 6 shows some aggregate moments for our four models and the UK, where we use HP-filtered data for 1993Q1-2008Q1 with a standard smoothing parameter of 1600.[45] With

[45]As the Bank of England adopted inflation targeting in 1992, we select 1993Q1 as the first time period. Moreover, we exclude the aftermath of the global financial crisis.

	UK	PPSI	SP	PPSP	PP
std. dev. of log output (%)	0.45	0.74	1.62	1.22	1.24
std. dev. of inflation (%)	0.25	0.14	0.37	0.32	0.59
autocorrelation of log output	0.68	0.92	0.96	0.95	0.89
autocorrelation of inflation	0.17	0.84	0.82	0.72	0.08
correlation of $\hat{Y}_t$ and $\hat{\pi}_t$	-0.19	-0.52	-0.76	-0.65	-0.52
correlation of $\hat{Y}_t$ and $\hat{\pi}_{t-4}$	-0.09	-0.60	-0.74	-0.63	-0.32
correlation of $\hat{Y}_t$ and $\hat{\pi}_{t+4}$	0.11	-0.37	-0.37	-0.25	-0.10

Table 6: Aggregate results (UK data for the time period 1993Q1 - 2008Q1).

regard to the standard deviation of log output, the PPSI model is closer to the data. The standard deviation of inflation predicted by the PPSI model is too low compared to the data, while it is too high for the SP model. In both models, the autocorrelations of inflation and log output are higher than in the data. In the data, log output and inflation are negatively correlated. All models are able to replicate this finding qualitatively, as business-cycle fluctuations are mostly driven by aggregate productivity shocks in all cases.[46]

Finally, Figure 4 shows the impulse responses to monetary shocks for the four models. In the SP model, a contractionary monetary-policy shock leads to a temporary increase in output after an initial drop. This can be explained by noting that the shock causes a drop in inflation and thereby a decrease in price dispersion, which is equivalent to an increase in aggregate productivity. Otherwise the dynamics for the PPSI and the SP models are qualitatively similar. Nevertheless it is important to distinguish between the two approaches as they have different implications for the welfare costs of inflation.

It may be surprising that the PPSI model implies only a moderate degree of inflation inertia and that the impulse response is not hump-shaped as in Mankiw and Reis (2002) and Trabandt (2007). This can be explained by noting that monetary policy is described by a Taylor rule rather than a money-growth rule (see Coibion (2006)). In the PP model, output is unaffected by monetary shocks. This confirms our previous claim that the aggregate dynamics of the PP model are equivalent to the ones of a flexible-price model.

[46] A variance decomposition yields that, in the PPSI model, approximately 70% of output fluctuations can be attributed to fluctuations in aggregate productivity. For the other three models, the respective number is around 95%.

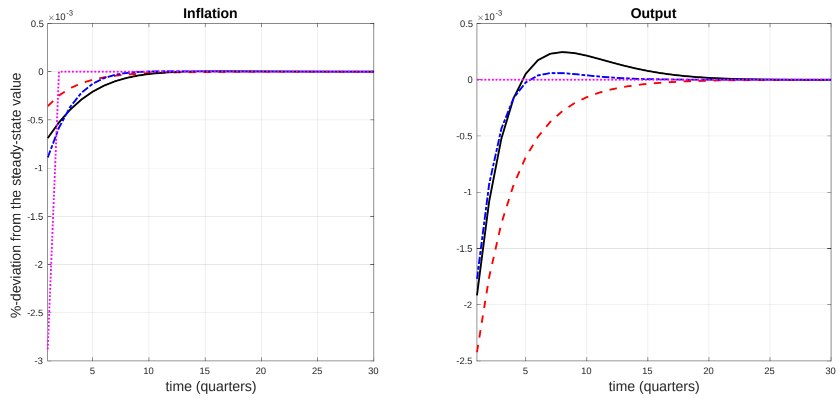

Figure 4: Impulse responses to monetary-policy shocks for the PPSI model (red dashed line), the SP model (black solid line), the PPSP model (blue dashed line), and PP model (purple dotted line).

10. Conclusion

Kashyap (1995), Blinder et al. (1998) and Levy et al. (2011) have identified the empirical regularity that price points are relevant for firms' price setting decisions. Based on this observation, Knotek (2016) has shown that price points rather than menu costs may be responsible for extended price spells. However, a model where price points are the only source of price stickiness has the implication that monetary policy has no real effects, which contradicts the widespread consensus in monetary economics that central banks can influence real output in the short run.

As a consequence, this paper has proposed a model featuring a prominent role for price points as well information stickiness. Due to the presence of sticky information, monetary policy has real effects in our model. At the same time, our model can reproduce many stylized facts of price-setting, which cannot be easily reconciled with time-dependent pricing models such as those based on Calvo pricing. For example, our model is in line with the findings that the frequency of price adjustment is positively related to inflation and that the magnitude of price decreases exceeds the size of increases. It is also compatible with the observation that previously chosen prices are revisited with non-negligible probability.

One can also look at our approach from a slightly different angle and interpret it as a way of making sticky-information models more consistent with empirical findings about price dynamics. For example, Maćkowiak and Wiederholt (2009, p. 798) note that their model of rational inattention is not compatible with spells of constant prices, unless additional frictions such as menu costs are included. The PP restriction proposed in this paper can be viewed as a simple alternative mechanism that generates sticky individual prices in models of rational inattention.

Our framework could also be used to examine the impact of a change in trend inflation on price dynamics. The PPSI model would entail that price changes are more frequent and have a smaller mean magnitude if the trend rate of inflation is raised in a comparative statics exercise.[47] This follows from the observation that the comparably small price adjustments that are necessary from time to time to catch up with increases in the price level occur more frequently when inflation is higher. By contrast, the SP model would predict that the frequency of price changes is not affected by changes in trend inflation and that the magnitude of price changes increases with inflation.[48] The evidence presented by Wulfsberg (2016) for Norway, namely that prices change more frequently and in smaller steps in periods of high inflation compared to periods of low inflation, appears to be more in line with the predictions of the PPSI model. Using our model to carefully examine how changes in trend inflation affect price dynamics would be an interesting avenue for future research.

[47] To be precise, this is true for small and moderate inflation. For very large inflation rates, almost all prices are raised every period. In such a situation, the size of price changes would increase with inflation.

[48] The literature on endogenous time-dependent pricing (see Bonomo and Carvalho (2004), for example) allows for the frequency of price adjustment to change in responses to changes in trend inflation. The specific prediction of the PPSI model, which would not typically arise in endogenous time-dependent models, is that the frequency of small price adjustment responds more strongly to changes in trend inflation than the frequency of large price adjustments.

Alvarez, F., Le Bihan, H., Lippi, F., 2016. The real effects of monetary shocks in sticky price models: a sufficient statistic approach. American Economic Review 106 (10), 2817–2851.

Ascari, G., Sbordone, A. M., 2014. The macroeconomics of trend inflation. Journal of Economic Literature 52 (3), 679–739.

Bils, M., Klenow, P. J., 2004. Some evidence on the importance of sticky prices. Journal of Political Economy 112 (5), 947–985.

Blinder, A. S., Canetti, E. R. D., Lebow, D. E., Rudd, J. B., 1998. Asking About Prices. Russel Sage Foundation.

Bonomo, M., Carvalho, C., 2004. Endogenous time-dependent rules and inflation inertia. Journal of Money, Credit and Banking 36 (6), 1015–1041.

Burstein, A. T., Hellwig, C., 2007. Prices and market shares in a menu cost model, NBER Working Paper #13455.

Calvo, G. A., 1983. Staggered prices in a utility-maximizing framework. Journal of Monetary Economics 12 (3), 383–398.

Chen, H., Levy, D., Snir, A., 2017. End of 9-endings, price recall, and price perceptions. Economics Letters 155, 157–163.

Coibion, O., 2006. Inflation inertia in sticky information models. Contributions in Macroeconomics 6 (1), 1–29.

Dhyne, E., Alvarez, L. J., Behan, H. L., Veronese, G., Dias, D., Hoffman, J., Jonker, N., Lünnemann, P., Rumler, F., Vilmunen, J., 2006. Price changes in the Euro area and the United States: Some facts from individual consumer price data. Journal of Economic Perspectives 20(2), 171–192.

Dupor, B., Kitamura, T., Tsuruga, T., 2010. Integrating sticky prices and sticky information. Review of Economics and Statistics 92 (3), 657–669.

Eggertsson, G. B., Garga, V., 2017. Sticky prices versus sticky information: Does it matter for policy paradoxes?, NBER Working Paper #23961.

Eichenbaum, M., Jaimovich, N., Rebelo, S., 2011. Reference prices, costs, and nominal rigidites. American Economic Review 101 (1), 234–262.

Eichenbaum, M., Jaimovich, N., Rebelo, S., Smith, J., 2014. How frequent are small price changes? American Economic Journal: Macroeconomics 6 (2), 137–55.

Gertler, M., Leahy, J., 2008. A Phillips curve with an Ss foundation. Journal of Political Economy 116 (3), 533–572.

Golosov, M., Lucas, R. E., 2007. Menu costs and Phillips curves. Journal of Political Economy 115 (2), 171–199.

Hamadi, T., Strudthoff, 2016. Are behavioral pricing tactics also present in the B2B context? Evidence from a complex chemical B2B product. Journal of Business Chemistry 13(1), 3–16.

Harrison, R., Oomen, Ö., 2010. Evaluating and estimating a DSGE model for the United Kingdom, Bank of England Working Paper #380.

Ilut, C. L., Valchev, R., Vincent, N., 2016. Paralyzed by fear: Rigid and discrete pricing under demand uncertainty, NBER working paper #22490.

Kashyap, A. K., 1995. Sticky prices: New evidence from retail catalogues. Quarterly Journal of Economics 110 (1), 245–274.

Kaufmann, D., Lein, S. M., 2013. Sticky prices or rational inattention – What can we learn from sectoral price data? European Economic Review 64, 384–394.

Kehoe, P., Midrigan, V., 2015. Prices are sticky after all. Journal of Monetary Economics 75, 35–53.

Kiley, M. T., 2007. A quantitative comparison of sticky-price and sticky-information models of price setting. Journal of Money, Credit and Banking 39 (s1), 101–125.

Kiley, M. T., 2016. Policy paradoxes in the new Keynesian model. Review of Economic Dynamics 21, 1–15.

Klenow, P. J., Kryvtsov, O., 2008. State-dependent or time-dependent pricing: Does it matter for recent U.S. inflation? Quarterly Journal of Economics 123 (3), 863–904.

Klenow, P. J., Malin, B. A., 2010. Microeconomic evidence on price-setting. In: Handbook of Monetary Economics. Amsterdam: Elsevier Science B.V., pp. 231–284.

Klenow, P. J., Willis, J. L., 2007. Sticky information and sticky prices. Journal of Monetary Economics 54 (Supplement), 79–99.

Knotek, E. S., 2008. Convenient prices, currency, and nominal rigidity: Theory with evidence from newspaper prices. Journal of Monetary Economics 55 (7), 1303 – 1316.

Knotek, E. S., 2016. The roles of price points and menu costs in price rigidity, working paper.

Kryvtsov, O., Vincent, N., February 2017. The cyclicality of sales and aggregate price flexibility, working paper.

Levy, D., Lee, D., Chen, H., Kauffman, R. J., Bergen, M., 2011. Price points and price rigidity. Review of Economics and Statistics 93 (4), 1417–1431.

Maćkowiak, B., Wiederholt, M., 2009. Optimal sticky prices under rational inattention. American Economic Review 99 (3), 769–803.

Mankiw, N. G., Reis, R., 2002. Sticky information versus sticky prices: A proposal to replace the new Keynesian Phillips curve. Quarterly Journal of Economics 117 (4), 1295–1328.

Matějka, F., 2015. Rigid pricing and rationally inattentive consumer. Journal of Economic Theory 158 (B), 656–678.

Matějka, F., 2016. Rationally inattentive seller: Sales and discrete pricing. Review of Economic Studies 83 (3), 1156–1188.

Midrigan, V., 2011. Menu costs, multiproduct firms, and aggregate fluctuations. Econometrica 79 (4), 1139–1180.

Monroe, K. B., 1973. Buyers' subjective perceptions of price. Journal of Marketing Research 10 (1), 77–80.

Nakamura, E., Steinsson, J., 2008. Five facts about prices: A reevaluation of menu cost models. Quarterly Journal of Economics 123 (4), 1415–1464.

Nakamura, E., Steinsson, J., 2013. Price rigidity: Microeconomic evidence and macroeconomic implications. Annual Review of Economics 5, 133–163.

Nakamura, E., Steinsson, J., Sun, P., Villar, D., 2018. The elusive costs of inflation: Price dispersion during the U.S. Great Inflation. Quarterly Journal of Economics 4 (1), 1933–1980.

Petrella, I., Santoro, E., de la Porte Simonsen, L., Aug. 2018. Time-varying price flexibility and inflation dynamics, working paper.

Sbordone, A. M., 2002. Prices and unit labor costs: a new test of price stickiness. Journal of Monetary Economics 49 (2), 265–292.

Trabandt, M., 2007. Sticky information vs sticky prices: A horse race in a DSGE framework, Sveriges Riksbank Working Paper #209.

Woodford, M., 2003. Interest and Prices: Foundations of a Theory of Monetary Policy. Princeton University Press, Princeton, New Jersey.

Wulfsberg, F., 2016. Inflation and price adjustments: Micro evidence from Norwegian consumer prices 1975–2004. American Economic Journal: Macroeconomics 8 (3), 175–194.