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Sticky prices vs. sticky information: A cross-country study of inflation dynamics

Christian Bredemeier, Henry Goecke

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Sticky Prices vs. Sticky Information: A Cross-Country Study of Inflation Dynamics

Christian Bredemeier
TU Dortmund University

Henry Goecke*
TU Dortmund University

Abstract

This paper compares sticky-price and sticky-information Phillips curves empirically considering inflation dynamics in eleven countries (the G7 and Scandinavia). We evaluate the models' abilities to match empirical second moments of inflation. Although overall model performance is similar, there is a strong systematic pattern in model performance by moment type. Sticky prices match unconditional moments of inflation dynamics clearly better while sticky information is considerably more successful in matching co-movements of inflation with demand.

Keywords: Phillips curve; Sticky information; Sticky prices
JEL Classification: E31; E32; E37

1 Introduction

Mankiw and Reis (2002) proposed sticky information as an alternative to the workhorse of monetary analysis, the sticky-price approach. Since then, many papers have studied the empirical performance of the sticky information Phillips curve and compared it to the sticky-price counterpart. This paper contributes to this horse race and performs a moment-matching exercise for the two concepts in eleven countries (the G7, Sweden, Denmark,

*Corresponding author, henry.goecke@tu-dortmund.de. Address: TU Dortmund University, Dept. of Economics, Applied Economics, Vogelpothsweg 87, D-44227 Dortmund.
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Finland, and Norway) revealing a clear pattern in model performance by moment type. Sticky prices are more successful in matching unconditional moments of inflation while it is the strength of sticky information to match demand reactions of inflation.

This insight relies on our broad view on the inflation process and on the cross-country perspective of the paper. While most previous papers have either considered full-information likelihoods (e.g. Andrés et al. 2005 and Laforte 2007) or specific moment types (e.g. Kiley 2007 and Korenok and Swanson 2007), we consider the inflation process broadly while still distinguishing between different types of moments. Revealing the regularity in model performance by moment type also relies on our cross-country perspective as it is systematic across countries but particularly pronounced in countries other than the US.

We compare the two Phillips curves in the framework of the Mankiw-Reis model (Mankiw and Reis 2002). Using this simple model has two advantages for our analysis. First, we can estimate the rest of the economy separately from the Phillips curves. This allows to compare the two Phillips curves in an identical environment, i.e. on a levelled playing field. The second advantage of the Mankiw-Reis model is that it is, for a given real side, solveable in closed form. This allows us to evaluate the stick-information model quantitatively without having to truncate the infinite stream of past expectations embedded in its Phillips curve. Such truncation has been shown not to be innocuous by Khan and Zhu (2002) and Verona and Wolters (2011).

Although the Mankiw-Reis model is very stylized, it seems sophisticated enough to capture inflation dynamics well. In our empirical analysis, we can reject equality between moments generated by the estimated models and empirical moments at 1% significance in only about 1% of the cases.

Our empirical procedure is a simulation-based moment evaluation. We estimate stochastic processes governing the dynamics of the output gap and solve for inflation as a rational-expectations equilibrium response to innovations in these processes. For a set of selected second moments of inflation, we generate distributions of model moments by repeated simulation of the model. For the different moments, we test whether equality of empirical and model moment can be rejected and compare the empirical performance of the two models on the ground of these tests.

Our results show that overall performance of the two models is rather similar. However, a more thorough look at model performance by moment type reveals systematic and interesting differences between models. Sticky prices perform clearly better than sticky information in matching unconditional moments of the inflation process. In every country, sticky prices match at least two thirds of the considered unconditional moments of inflation more closely than sticky information. Over all countries, sticky prices are more successful in about 85% of the unconditional moments.

By contrast, it is the strength of the sticky-information model to match the empirical co-movements of inflation and demand. In this domain, sticky information matches about 80% of the considered moments more closely than sticky prices. Considering the co-movement of inflation and supply, both models perform well and similarly with sticky prices being slightly more successful. To sum up the relative model performances by moment type, if one is predominantly interested in matching unconditional moments of inflation dynamics, sticky prices should be the concept of choice. Researchers who focus on co-movements of inflation with demand may obtain better results applying sticky information.

Our results fit well into those of the literature. They allow to shed some light on the mixed evidence revealed by previous studies when sorting studies by the moments considered. Similarly to the Mankiw-Reis model, Kiley (2007), Korenok (2008), and Korenok et al. (2008) work in models which consist of a Phillips curve and reduced-form equations for the rest of the economy. Kiley (2007) and Korenok (2008) only consider supply-side innovations and find that sticky prices perform better than sticky information in this domain. The cross-country study of Korenok et al. (2008) focusses on unconditional moments of inflation dynamics and find that sticky prices is more successful. Both findings are in line with our results as we determine matching the co-movement of inflation with demand being the strength of the sticky-information approach.

Opposed to our closed-form expectations approach, Coibion (2010), Ciobîcă (2010), and Dupor et al. (2010) perform single equation evaluations of the competing Phillips curves determining the expectation terms outside the model. Focussing on the predictive power of the Phillips curves for inflation rather than on co-movements with supply or demand, sticky prices dominate sticky information empirically in the results of these three papers. By contrast, Coibion and Gorodnichenko (2012) find that the relative strength of sticky information is to match the inflation response to demand innovations, as also shown in our paper.

A further group of papers compare the different Phillips curves within complete DSGE models. Therein, expectations are rational but the choice of the Phillips curve affects the estimates for the other parts of the model. Andrés et al. (2005), Paustian and Pytlarczyk (2006), and Laforte (2007) base their evaluations on the models' likelihoods. In line with our results, there is no clear picture when considering all model moments jointly with the results of two papers supporting sticky prices (Andrés et al. 2005 and Paustian and Pytlarczyk 2006) and one paper supporting sticky information (Laforte 2007).

By contrast, Korenok and Swanson (2007) and Abbott (2010) evaluate models by means of impulse responses. In line with our results, both papers find that sticky information matches co-movements to demand better than sticky prices. Also Carrillo (2012) identifies the reactions to demand innovation as the strength of the sticky-information approach, although, in his results, it performs almost equally as sticky prices in this domain.

Kiley (2007) and Dupor et al. (2010) also allow for combinations of sticky prices and sticky information which dominate the pure versions further confirming the impression that both concepts have empirical support. Similarly, sticky-price Phillips curves with indexation or ad-hoc lags of inflation are also shown to perform well (see e.g. Kiley 2007, Korenok and Swanson 2007, Korenok et al. 2008, and Abbott 2010).

The remainder of the paper is organized as follows. Section 2 presents the models. Our empirical strategy is described in Section 3. The empirical results are presented in in Section 4. Finally, Section 5 concludes.

2 Models

Phillips curves. We compare the concepts of sticky information and sticky prices which result in different Phillips curves. We close the models identically in the way proposed by Mankiw and Reis (2002). Also the particular forms of the two Phillips curves is taken from Mankiw and Reis (2002).

The sticky-price Phillips curve takes the form

$$\pi_t = \left[\frac{\alpha\lambda^2}{1-\lambda}\right] y_t + E_t \pi_{t+1}, \tag{1}$$

where π_t denotes inflation, y_t is the log output gap and E_t is the expectations operator based on the information set of period t. The parameter α is a measure of real rigidities that measures the dependency of an individual firm's optimal price on the output gap. The parameter λ denotes the fraction of prices changed in every period and is a measure of nominal rigidity.

The sticky-information Phillips curve takes the form

$$\pi_t = \left[\frac{\alpha\lambda}{1-\lambda}\right] y_t + \lambda \sum_{j=0}^{\infty} (1-\lambda)^j E_{t-1-j} \left(\pi_t + \alpha \Delta y_t\right), \tag{2}$$

where Δ is the difference operator, i.e. $\Delta y_t = y_t - y_{t-1}$. Here, λ is a measure of price rigidity which measures the fraction of firms receiving new information in each period.

The main difference between the two Phillips curves (1) and (2) is the presence of different expectation terms. As equation (1) states, in the sticky-price model, inflation depends on current expectations of future inflation which is the information used by firms that currently change prices. The sticky-information Phillips curve (2) contains all past expectations of current inflation reflecting that a fraction of firms change prices based on obsolete information of different age.

Closing the Models. The Phillips curves (1) and (2) represent a relationship between two endogenous variables, inflation π_t and the log output gap y_t. In order to close the model, a second relationship between these two variables is needed. Assuming that natural output is equal to labor productivity, the log output gap y_t can be written as

$$y_t = m_t - p_t - a_t,$$

where m_t is log nominal income, p_t is the log price level, and a_t is the log labor productivity. We follow the empirical analysis of Mankiw and Reis (2002), Reis (2006), and Mankiw and Reis (2011) and use their assumptions that demand and supply are exogenous to inflation and that they follow independent stochastic processes. We write changes in demand and supply, Δm_t and Δa_t, as their moving-average representations, $\Delta a_t = \sum_{i=0}^{\infty} \omega_i \varepsilon_{t-i}^a$ and $\Delta m_t = \sum_{i=0}^{\infty} \chi_i \varepsilon_{t-i}^m$.

By estimating the processes for demand and supply, our empirical procedure captures any structure in the data except from inflation feedbacks. It is important to note that these feedbacks are missed equally in both models. Furthermore, our modeling strategy ensures that the model can be estimated recursively and hence the choice of the Phillips curve does not influence estimates for other equations of the model. This is a major advantage of the Mankiw-Reis model for our analysis as, therein, we can compare sticky information and sticky prices in an otherwise identical model.

Eventhough it is very stylized, the Mankiw-Reis model seems sophisticated enough to capture empirical inflation dynamics well. In our empirical analysis, we can reject equality between model moments and empirical moments at 1% significance in only 1% of the cases.

Solving the Models. Both, the sticky-information model (SI) and the sticky-price model (SP), consist of a Phillips curve and the exogenous stochastic processes for demand and supply growth described above. Demand and supply shocks are thus the only driving forces of dynamics in the models. Inflation is therefore a moving average of these shocks,

$$\pi_t = \sum_{i=0}^{\infty} \gamma_i^z \varepsilon_{t-i}^m + \sum_{i=0}^{\infty} \xi_i^z \varepsilon_{t-i}^a, \tag{3}$$

where $z = SI, SP$. We solve for the coefficients γ_i^{SI} and ξ_i^{SI}, or γ_i^{SP} and ξ_i^{SP} respectively, using the method of undetermined coefficients. In the sticky information model, the coefficients on demand shocks fulfill $\gamma_0^{SI} = \frac{\alpha\lambda}{1-\lambda+\alpha\lambda}$ and $\gamma_k^{SI} = \alpha\lambda\left(1-\lambda\left(1-\alpha\right)\sum_{i=0}^{k}\left(1-\lambda\right)^i\right)^{-1}\cdot\left[1-\sum_{i=0}^{k-1}\gamma_i^{SI}+\sum_{i=1}^{k}\chi_i+\chi_k\sum_{i=1}^{k}\left(1-\lambda\right)^i\right]$ for $k>0$. In the sticky-price model, the inflation response to demand shocks is described by $\gamma_0^{SP} = (1-\theta)\sum_{i=0}^{\infty}\theta^i\chi_i$ and $\gamma_k^{SP} = (\theta-1)\left\{\sum_{j=0}^{k-1}\gamma_j^{SP}-\sum_{i=0}^{k-1}\chi_i-\sum_{i=k}^{\infty}\chi_i\theta^{i-k}\right\}$ for $k>0$. The coefficients on supply shocks are equivalent except for wearing the opposite sign and incorporating the MA coefficients of supply shocks ω_i's instead of the χ_i's.[1]

It is a second major advantage of the Mankiw-Reis model that we can solve (3) in closed form for any given processes found for demand and supply. This allows to evaluate predicted inflation of the sticky-information models without having to truncate the infinite stream of past expectations embedded in its Phillips curve. Such truncation has been shown not to be innocuous by Khan and Zhu (2002) and Verona and Wolters (2011).

3 Empirical Strategy

Our empirical procedure is a simulation-based moment evaluation. For each country, we first estimate stochastic processes governing the dynamics of the output gap. Then, we determine model-predicted inflation as a rational-expectations equilibrium response to demand and supply shocks, as in Reis (2006). We simulate the model on a quarterly basis and evaluate the dynamics of annual changes, i.e. we target the dynamics of $\Delta_4 p_t = p_t - p_{t-4}$.[2] In order to determine whether model moments differ significantly from their empirical counterparts, we determine the probability distribution of the empirical moments by a bootstrapping method and, for that of the model mo-

[1] A detailed derivation can be found in the Appendix to the previous version of this paper, Bredemeier and Goecke (2011).

[2] Considering annual changes extenuates potential measurement errors in quarterly seasonally adjusted data. Using quarterly changes, second moments of inflation dynamics in some countries differ substantially from what is observed in the US. For annual changes, moments are much more similar across countries.

ments, we generate a probability distribution by repeated model simulation. Using these distributions, we perform tests of significant difference to the empirical moments for each model moment. Our evaluation bases on the p-values of these tests.

We take a broad perspective on the inflation process. Our set of considered moments therefore includes unconditional moments of inflation dynamics (standard deviation and auto-correlation function) as well as measures of the co-movements with supply and demand (cross-correlation with contemporaneous levels, a lead and four lags). We evaluate 18 moments per model and country, six of each moment type. Considering two models in eleven countries, this gives a total of 396 moments and 132 per moment type.

While we estimate the stochastic processes governing the dynamics of the output gap, we set the parameters of the Phillips curves. We use standard levels of stickiness and real rigidities and take the parameter choices of Reis (2006), $\alpha = 0.11$ and $\lambda = 0.25$.[3] In a previous version of this paper, we have also considered model versions in which we estimated α and λ using the method of simulated moments. Although results differed in detail, the overall pattern in relative model performance by moment type is robust across specifications.

Formally, for each country c (US, Japan, Germany, France, UK, Italy, Canada, Sweden, Denmark, Finland, Norway) and model z (sticky information, sticky prices), we proceed as follows:

1. We first estimate processes for nominal income growth and productivity growth from the data. In any country and for both time series, we start with estimating the parameters of an AR(4) process by OLS. If the coefficient on the last lag is not significantly different from zero, we drop that lag and re-estimate an auto-regressive process of order 3. We drop insignificant lags until we arrive at a process with a significant last lag (sequential t-testing). Having found such an auto-regressive process, we invert it into its MA representation with the coefficients

[3]Several cross-country studies estimating these parameters have found very similar values (see e.g. Khan and Zhu 2002 and Döpke et al. 2008).

$\{\chi_i^c\}$ and $\{\omega_i^c\}$ and the innovation variances $\sigma_{m,c}^2$ and $\sigma_{a,c}^2$ of nominal income growth and productivity growth, respectively.

2. Using the values for the coefficients $\{\chi_i^c\}$ and $\{\omega_i^c\}$ and the parameters α and λ, we calculate the coefficients $\{\gamma_i^{c,z}\}$ and $\{\xi_i^{c,z}\}$ in the MA representation of inflation (3).

3. Combining the sequence of residuals derived from the estimation in step 1 with the MA coefficients in (3) derived in step 2, we calculate a sequence of quarterly inflation rates $\{\Delta p_t^{c,z}\}$ predicted by model z for country c. We then calculate the selected second moments of corresponding annual changes.

4. In order to evaluate the statistical properties of the model moments, we simulate the model 10,000 times. In each simulation, we draw sequences of innovations $\{\varepsilon_t^{m,c}\}$ and $\{\varepsilon_t^{a,c}\}$ from the estimated distributions of supply and demand shocks and feed them into the model. Combining the innovations $\{\varepsilon_t^{m,c}\}$ and $\{\varepsilon_t^{a,c}\}$ and the MA coefficients of inflation $\{\gamma_i^{c,z}\}$ and $\{\xi_i^{c,z}\}$, we generate a sequence of predicted inflation rates $\{\Delta p_t^{c,z}\}$.

   For each simulation, we calculate the considered second moments. We thus generate a distribution of model moments by simulation. For each moment $x \in X$, we then estimate a density function $f_x^{c,z}\left(x|\alpha, \lambda, \{\chi_i^c\}_{i=0}^{\infty}, \sigma_{m,c}^2, \{\omega_i^c\}_{i=0}^{\infty}, \sigma_{a,c}^2\right)$ from the 10,000 generated observations using Maximum Likelihood. We use the function $f_x^{c,z}\left(x|\alpha, \lambda, \{\chi_i^c\}_{i=0}^{\infty}, \sigma_{m,c}^2, \{\omega_i^c\}_{i=0}^{\infty}, \sigma_{a,c}^2\right)$ to test for difference between empirical moment $x^{c,data}$ and model moment $x^{c,z}$. To determine the standard deviations of the empirical moments we use the method of moving blocks bootstrap.

Data. In our analysis, we use quarterly data on nominal income, labor productivity, and consumer price indices. Our data stem from the OECD, Datastream, and the national statistical offices of the considered countries. Data sources and details are summarized in Table 1.

	Price level	Nominal income	Productivity
United States (1954Q1-2003Q4)	Bureau of Labor Statistics; Series Id: CUUR0000SA0	Bureau of Economic Analysis; Table 1.1.5.	Bureau of Labor Statistics; Output per hour; Non-farming Sector; 1992=100
Japan (1970Q1-2008Q4)	OECD; Consumer prices – all items; Index 2005=100	DSI Data Service; Nominal Gross Domestic Product (original series, seasonally adjusted)	Datastream; Labour productivity; Total economy
Germany (1970Q1-2008Q4)	OECD; Consumer prices – all items; Index 2005=100	Federal Statistical Office; nom. GDP, seasonally adj., before 1990 West Germany, linear extrapolation of growth rate in 1990Q1	Bundesbank; Productivity per hour; Seasonally adjustted; Index 1995=100
France (1978Q1-2008Q4)	OECD; Consumer prices – all items; Index 2005=100	National Institute of Statistics and Economic Studies; GDP, all sectors, all products, current prices	National Institute of Statistics and Economic Studies; GDP per employed person
United Kingdom (1959Q1-2008Q4)	OECD; Consumer prices – all items; Index 2005=100	Calculated as price level (left) times real GDP (Office for National Statistics; ABMI)	Office for National Statistics UK; A4YM
Italy (1980Q1-2008Q4)	Datastream; Code: 319999669	Datastream: Code 316875096	Datastream; Code: 318599977
Canada (1961Q1-2008Q4)	OECD; Consumer prices – all items; Index 2005=100	Calculated as price level (left) times real GDP (Datastream; Canada GDP at market prices (chained, SA, AR) CONA)	Datastream; Code: CNOCFPROG
Sweden (1970Q1-2008Q4)	Datastream; Code: 359997773	OECD; Millions of national currency, current prices, seasonally adjusted	Calculated as real GDP (M/P) dived by employment (OECD, civilian employment, all persons)
Denmark (1995Q1-2008Q4)	Datastream; Code: 281002001	Datastream; Code: 630030110	Datastream; Code: 289996578
Finland (1975Q1-2008Q4)	Datastream; Code: 452000261	Datastream; Code: 452000500	Calculated as real GDP (M/P) dived by employment (OECD, civilian employment, all persons)
Norway (1978Q1-2008Q4)	Datastream; Code: 349997771	Datastream; Code: 348600367	Datastream; Code: 40143694

Table 1: Data sources and details (countries ordered by population size).

4 Results

Our empirical analysis starts with estimating the auto-regressive processes for demand and productivity growth in the eleven countries in our sample. In 15 of the 22 cases, higher-order processes are needed to describe the dynamics in productivity and demand growth in the different countries. The estimated auto-regressive processes are reported in Table 2.

	nominal income growth						productivity growth					
	cons *·100*	*t-1*	*t-2*	*t-3*	*t-4*	σ_a^2 $\cdot 10^4$	*cons* *·100*	*t-1*	*t-2*	*t-3*	*t-4*	σ_m^2 $\cdot 10^4$
United States	1.05	0.39				0.81	0.54					0.72
	(0.13)	(0.06)					(0.06)					
Japan	0.10	0.21	0.37	0.29		1.11	0.14	0.52	0.18	0.02	-0.27	3.31
	(0.12)	(0.08)	(0.07)	(0.08)			(0.15)	(0.09)	(0.11)	(0.11)	(0.09)	
Germany	0.32	0.02	0.14	0.17	0.35	0.93	0.91					1.60
	(0.16)	(0.08)	(0.08)	(0.08)	(0.08)		(0.10)					
France	0.13	0.48	0.40			0.28	0.28	-0.03	0.23			0.18
	(0.09)	(0.09)	(0.09)				(0.06	(0.09)	(0.09)			
United Kingdom	0.38	0.14	0.13	0.08	0.45	1.46	0.50					0.79
	(0.19)	(0.07)	(0.07)	(0.07)	(0.07)		(0.06)					
Italy	0.11	0.08	0.20	0.11	0.49	0.99	0.41					4.31
	(0.18)	(0.08)	(0.09)	(0.09)	(0.09)		(0.19)					
Canada	0.57	0.48	-0.09	0.29		0.90	0.27	-0.14	0.04	0.18		0.53
	(0.17)	(0.07)	(0.08)	(0.07)			(0.07)	(0.07)	(0.07)	(0.07)		
Sweden	1.16	-0.19	0.26	0.29		3.00	0.86	-0.34	-0.42			4.36
	(0.30)	(0.08)	(0.08)	(0.08)			(0.18)	(0.07)	(0.07)			
Denmark	2.07	-0.63	-0.43	-0.24	0.42	2.17	1.05	-0.91	-0.66	-0.70		2.82
	(0.60)	(0.14)	(0.16)	(0.16)	(0.14)		(0.25)	(0.10)	(0.13)	(0.09)		
Finland	0.61	0.10	-0.07	-0.08	0.88	4.48	0.82	-0.36	-0.33	-0.33	0.62	4.19
	(0.33)	(0.04)	(0.04)	(0.04)	(0.04)		(0.22)	(0.06)	(0.06)	(0.06)	(0.06)	
Norway	1.96					4.55	0.57	-0.32				1.86
	(0.19)						(0.13)	(0.09)				

Table 2: Estimated coefficients and shock variances for productivity and nominal income growth processes (countries ordered by population size).

Table 3 shows a first summary of the results of our moments-matching exercise. The table disentangles model performance by moment type and reports for how many moments (of the 66 per model and moment type) we can reject equality between the model moment and the empirical moment for different levels of significance. Table 4 shows a relative measure of model performance by country and moment type. The table reports the number of moments for which, under the respective model, the p-value of the model-equals-data-moment test is larger than under the other model i.e. that are matched better.

Table 5 shows the results in more detail and reports the exact model-generated moments, their empirical counterparts as well as the p-values of the equality tests. P-values are shown in parentheses and *, **, and *** indicate statistically significant differences between model and data moment at 10%, 5%, 1% significance, respectively. A p-value in italic indicates that this value is lower than that of the other model, i.e. a poorer match.

The results summarized in Table 3 confirm our view that the Mankiw-Reis

	unconditional moments		co-movements to demand		co-movements to supply	
	S.I.	S.P.	S.I.	S.P.	S.I.	S.P.
moments rejected at 10%	7	4	1	3	3	2
moments rejected at 5%	6	4	0	3	1	0
moments rejected at 1%	3	1	0	0	0	0

Table 3: Numbers of rejected moments by moment type.

model is sufficiently sophisticated for our analysis. At 1% significance, we can reject equality between model-generated moments and statistical counterparts in only four of the 396 cases, i.e. in about 1%. Overall model performance is similar. Considering the 5% and 10% significance levels, the two models show about the same number of rejected moments. Also the total numbers of moments matched more closely are about the same for both models, see column "total" in Table 4. Sticky information is more successful in about 47% of the moments considered while sticky prices match 53% of the moments better.

Also considering the overall model performance by country, the evidence is mixed. Sticky information performs better in three countries (Japan, France, Canada) while it is dominated by sticky prices in four countries (UK, Italy, Sweden, Norway). We observe a draw in terms of moments matched more closely in four countries (US, Germany, Denmark, Finland).

However, the results show a clear pattern in model performance when it is considered by moment type. Sticky prices outperform sticky information with respect to unconditional moments of inflation while sticky information is clearly more successful in matching the co-movement of inflation and demand.

The first type of second moments we consider are unconditional moments of inflation, i.e. its standard deviation and auto-correlation function. In this domain, sticky information has the higher number of rejected moments at any conventional level of significance (see Table 3). Furthermore, sticky prices match the overwhelming majority of moments closer than sticky information. This results holds both overall as well as in any single country (see column "unconditional moments" in Table 4). Over all countries, sticky prices display the higher p-value indicating a relatively good match in 56 of

	unconditional moments		co-movements to demand		co-movements to supply		total	
	S.I.	S.P.	S.I.	S.P.	S.I.	S.P.	S.I.	S.P.
United States	1	5	3	3	5	1	9	9
Japan	0	6	6	0	4	2	10	8
Germany	1	5	5	1	3	3	9	9
France	0	6	6	0	6	0	12	6
United Kingdom	1	5	3	3	0	6	4	14
Italy	0	6	5	1	1	5	6	12
Canada	0	6	5	1	6	0	11	7
Sweden	2	4	4	2	1	5	7	11
Denmark	2	4	4	2	3	3	9	9
Finland	2	4	6	0	1	5	9	9
Norway	1	5	6	0	0	6	7	11
total	10	56	53	13	31	35	94	104

Table 4: Sticky information vs. sticky prices. Number of moments matched more closely by country and moment type.

the 66 unconditional moments (85%). In no single country, sticky information matches more than two unconditional moment closer than sticky prices. In most of the countries, the picture is even clearer with sticky prices matching five (US, Germany, UK, Norway) or all six (Japan, France, Italy, Canada) moments more closely than sticky information. As for the standard deviation and its auto-correlation function, we can thus summarize that these moments are matched clearly better using the sticky-price Phillips curve.

The picture is exactly reverse in the group of moments that measure the co-movement of inflation and demand. Here, sticky prices display more rejected moments at 10% and 5% significance (see Table 3). Also comparing the p-values of a specific moment and country across models, the dominance of the sticky information in this domain is evident (see column "co-movements to demand" in Table 4). Over all countries, sticky information matches 53 of the 66 moments better than sticky prices, i.e. over 80%. Considering the models' match to the empirical co-movement of inflation and demand, models perform similarly only in the US and the UK. In each of the other nine countries, sticky information matches the majority of moments more closely than sticky prices. In four countries (Japan, France, Finland, Norway), the dominance of sticky information even manifests in a 6:0 sweep. These results

	United States			Japan			Germany		
	S.I.	S.P.	data	S.I.	S.P.	data	S.I.	S.P.	data
$\mathrm{S.D.}(\Delta_4 p_t)$	0.0228 [0.8419]	0.0211 *[0.4655]*	0.0235	0.1477^{***} *[0.0001]*	0.0386 [0.4568]	0.0221	0.0325^{*} *[0.0560]*	0.0244 [0.2345]	0.0158
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 p_{t-1})$	0.9968 *[0.8109]*	0.9960 [0.8286]	0.9864	0.9993 *[0.4268]*	0.9935 [0.5022]	0.9592	0.9953 *[0.3834]*	0.9947 [0.3971]	0.9503
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 p_{t-2})$	0.9872 *[0.7330]*	0.9853 [0.7636]	0.9577	0.9976 *[0.3344]*	0.9836 [0.4362]	0.9078	0.9820 *[0.3274]*	0.9825 [0.3418]	0.8825
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 p_{t-3})$	0.9720 *[0.6851]*	0.9695 [0.7222]	0.9187	0.9954 *[0.2936]*	0.9737 [0.4088]	0.8520	0.9605 *[0.3148]*	0.9666 [0.3194]	0.8072
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 p_{t-4})$	0.9519 *[0.4818]*	0.9500 [0.5746]	0.8737	0.9930 *[0.0517]*	0.9657 [0.1857]	0.7876	0.9320 *[0.1075]*	0.9492 [0.1196]	0.7200
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 p_{t-5})$	0.9279 *[0.4428]*	0.9284 [0.5291]	0.8306	0.9908^{**} *[0.0253]*	0.9618 [0.1615]	0.7465	0.8979 [0.1150]	0.9328 *[0.1035]*	0.6595
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 m_t)$	0.5258 *[0.7097]*	0.5671 [0.8708]	0.5883	0.7166 [0.8809]	0.8115 *[0.5454]*	0.7598	0.6036 [0.4684]	0.7211 *[0.0476]*	0.4460
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 m_{t-1})$	0.5633 *[0.7284]*	0.6266 [0.9297]	0.6167	0.7274 [0.8489]	0.8270 *[0.5797]*	0.7806	0.6417 [0.5586]	0.7367^{*} *[0.0678]*	0.5254
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 m_{t-2})$	0.6079 [0.8089]	0.6752 *[0.8019]*	0.6447	0.7426 [0.8648]	0.8410 *[0.6542]*	0.7907	0.6718 [0.6450]	0.7350 *[0.2345]*	0.5828
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 m_{t-3})$	0.6481 [0.8931]	0.7114 *[0.7801]*	0.6703	0.7647 [0.9173]	0.8571 *[0.6846]*	0.7950	0.6987 [0.6518]	0.7261 *[0.4641]*	0.6072
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 m_{t-4})$	0.6851 [0.9436]	0.7346 *[0.7567]*	0.6948	0.7802 [0.9504]	0.8635 *[0.6072]*	0.7970	0.7237 *[0.5100]*	0.7046 [0.5192]	0.6145
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 m_{t+1})$	0.4960 *[0.7503]*	0.5163 [0.8112]	0.5523	0.7000 [0.8988]	0.7785 *[0.7347]*	0.7382	0.5742 [0.3829]	0.6902^{*} *[0.0512]*	0.3775
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 a_t)$	-0.4026 [0.8766]	-0.4691 *[0.8223]*	-0.4310	0.1585 *[0.8320]*	0.0653 [0.9234]	0.0903	-0.1612 [0.4816]	-0.1769 *[0.4355]*	-0.0059
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 a_{t-1})$	-0.4162 [0.9302]	-0.4659 *[0.8227]*	-0.4312	0.1303 [0.8829]	0.0534 *[0.6052]*	0.1708	-0.2215 *[0.2982]*	-0.2171 [0.3011]	-0.0060
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 a_{t-2})$	-0.4082 [0.9750]	-0.4389 *[0.8152]*	-0.4029	0.1734 [0.7280]	0.1228 *[0.5282]*	0.2620	-0.2347 *[0.3009]*	-0.2167 [0.3362]	-0.0214
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 a_{t-3})$	-0.4021 [0.8471]	-0.4048 *[0.8246]*	-0.3676	0.2257 [0.7048]	0.1920 *[0.5804]*	0.3261	-0.2049 *[0.5124]*	-0.1898 [0.5534]	-0.0613
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 a_{t-4})$	-0.3944 *[0.6579]*	-0.3692 [0.7637]	-0.3229	0.2857 [0.7603]	0.2498 *[0.6291]*	0.3642	-0.1450 [0.7254]	-0.1577 *[0.6771]*	-0.0733
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 a_{t+1})$	-0.3890 [0.8737]	-0.4609 *[0.8001]*	-0.4176	0.1541 *[0.5451]*	0.0669 [0.6581]	-0.0221	-0.1360 [0.6937]	-0.1670 *[0.5842]*	-0.0549
	France			**United Kingdom**			**Italy**		
	S.I.	S.P.	data	S.I.	S.P.	data	S.I.	S.P.	data
$\mathrm{S.D.}(\Delta_4 p_t)$	0.1983^{***} *[0.0000]*	0.0369^{**} [0.0103]	0.0109	0.0475 [0.7975]	0.0401 *[0.2643]*	0.0500	0.5302^{***} *[0.0000]*	0.0805^{**} [0.0508]	0.0156
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 p_{t-1})$	0.9999 *[0.1876]*	0.9971 [0.2065]	0.9253	0.9954 *[0.6280]*	0.9917 [0.6924]	0.9738	0.9999 *[0.6539]*	0.9979 [0.6825]	0.9739
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 p_{t-2})$	0.9996 *[0.1640]*	0.9913 [0.1927]	0.8454	0.9824 *[0.4896]*	0.9708 [0.5903]	0.9230	0.9998 *[0.5463]*	0.9931 [0.5954]	0.9309
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 p_{t-3})$	0.9992 *[0.1738]*	0.9848 [0.2106]	0.7749	0.9617 *[0.4360]*	0.9434 [0.5443]	0.8617	0.9995 *[0.4724]*	0.9876 [0.5536]	0.8768
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 p_{t-4})$	0.9986^{**} *[0.0178]*	0.9796^{**} [0.0379]	0.7108	0.9343 *[0.2218]*	0.9153 [0.3609]	0.8042	0.9990 *[0.1686]*	0.9829 [0.2845]	0.8271
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 p_{t-5})$	0.9979^{**} *[0.0151]*	0.9769^{**} [0.0425]	0.7065	0.9018 *[0.2410]*	0.8914 [0.3499]	0.7623	0.9982 *[0.0904]*	0.9800 [0.2213]	0.7893
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 m_t)$	0.6409 [0.6511]	0.7806 *[0.2991]*	0.4693	0.7799 *[0.4558]*	0.9197 [0.9720]	0.9164	0.7794 [0.9314]	0.8333 *[0.7632]*	0.7413
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 m_{t-1})$	0.6521 [0.6439]	0.7874 *[0.2742]*	0.4743	0.8155 *[0.5635]*	0.9481 [0.6948]	0.9143	0.7882 [0.9939]	0.8358 *[0.8609]*	0.7848
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 m_{t-2})$	0.6551 [0.7273]	0.7712 *[0.3979]*	0.5172	0.8370 [0.8003]	0.9509 *[0.5015]*	0.8798	0.7853 [0.9811]	0.8182 *[0.9417]*	0.7962
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 m_{t-3})$	0.6775 [0.7885]	0.7588 *[0.5601]*	0.5667	0.8570 [0.9181]	0.9337 *[0.4916]*	0.8386	0.7875 [0.9976]	0.7998 *[0.9667]*	0.7861
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 m_{t-4})$	0.7043 [0.8547]	0.7506 *[0.7098]*	0.6315	0.8722 [0.6307]	0.9014 *[0.3936]*	0.8016	0.7925 *[0.9620]*	0.7811 [0.9733]	0.7705
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 m_{t+1})$	0.6531 [0.5980]	0.7591 *[0.3289]*	0.4500	0.7632 *[0.5409]*	0.8699 [0.8951]	0.8865	0.7904 [0.8381]	0.8255 *[0.6997]*	0.6989
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 a_t)$	0.3751 [0.6917]	0.4788 *[0.4243]*	0.2626	-0.0112 *[0.2629]*	-0.1186 [0.5560]	-0.2325	0.3005 *[0.8381]*	0.2898 [0.8681]	0.2456
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 a_{t-1})$	0.3777 [0.6420]	0.4847 *[0.3727]*	0.2499	-0.0528 *[0.2814]*	-0.1458 [0.5625]	-0.2462	0.3026 *[0.8985]*	0.2590 [0.9639]	0.2703
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 a_{t-2})$	0.3715 [0.6566]	0.4700 *[0.4115]*	0.2488	-0.0943 *[0.3533]*	-0.1658 [0.5892]	-0.2575	0.3125 *[0.8800]*	0.2403 [0.8944]	0.2738
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 a_{t-3})$	0.3123 [0.6739]	0.4028 *[0.4610]*	0.1899	-0.1287 *[0.5241]*	-0.1787 [0.7054]	-0.2473	0.3021 [0.8981]	0.2185 *[0.8598]*	0.2667
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 a_{t-4})$	0.3106 [0.7546]	0.3725 *[0.5909]*	0.2256	-0.1519 *[0.6451]*	-0.1988 [0.8466]	-0.2315	0.2956 *[0.8409]*	0.2112 [0.8953]	0.2442
$\mathrm{corr}(\Delta_4 p_t, \Delta_4 a_{t+1})$	0.4027 [0.6413]	0.4606 *[0.4725]*	0.2753	0.0261 *[0.2455]*	-0.1161 [0.7011]	-0.1851	0.2961 [0.7908]	0.3143 *[0.7334]*	0.2285

Table 5: Detailed results by country.

	Canada			Sweden			Denmark		
	S.I.	S.P.	data	S.I.	S.P.	data	S.I.	S.P.	data
S.D.($\Delta_4 p_t$)	0.0330 *[0.6783]*	0.0301 [0.8901]	0.0308	0.0384 [0.9852]	0.0381 *[0.9549]*	0.0385	0.0866 *[0.2442]*	0.0375 [0.6063]	0.0077
corr($\Delta_4 p_t$, $\Delta_4 p_{t-1}$)	0.9961 *[0.6043]*	0.9944 [0.6358]	0.9727	0.9964 [0.5447]	0.9972 *[0.5402]*	0.9649	0.5284 [0.4993]	0.9666 *[0.3137]*	0.8042
corr($\Delta_4 p_t$, $\Delta_4 p_{t-2}$)	0.9851 *[0.5522]*	0.9809 [0.5973]	0.9321	0.9880 *[0.4700]*	0.9901 [0.4758]	0.9151	0.7472 [0.5772]	0.7625 *[0.3708]*	0.5069
corr($\Delta_4 p_t$, $\Delta_4 p_{t-3}$)	0.9675 *[0.5333]*	0.9631 [0.5758]	0.8842	0.9752 *[0.4242]*	0.9804 [0.4320]	0.8541	0.3583 *[0.5476]*	0.2819 [0.6691]	0.1076
corr($\Delta_4 p_t$, $\Delta_4 p_{t-4}$)	0.9442 *[0.3361]*	0.9445 [0.3965]	0.8339	0.9576 *[0.2004]*	0.9695 [0.2272]	0.7877	0.3866** *[0.0154]*	-0.0772 [0.6571]	-0.2781
corr($\Delta_4 p_t$, $\Delta_4 p_{t-5}$)	0.9168 *[0.3822]*	0.9278 [0.3984]	0.8017	0.9386 *[0.2302]*	0.9589 [0.2326]	0.7546	0.0161 *[0.3573]*	-0.3255 [0.8964]	-0.3881
corr($\Delta_4 p_t$, $\Delta_4 m_t$)	0.7427 [0.7293]	0.8485 *[0.6836]*	0.8020	0.6485 *[0.6349]*	0.7621 [0.7730]	0.7292	-0.4540 *[0.1019]*	0.1782 [0.5205]	-0.0256
corr($\Delta_4 p_t$, $\Delta_4 m_{t-1}$)	0.7812 [0.7936]	0.8746 *[0.5822]*	0.8214	0.6843 [0.7280]	0.7948 *[0.5914]*	0.7408	-0.1939* *[0.0570]*	0.4644 [0.5817]	0.2903
corr($\Delta_4 p_t$, $\Delta_4 m_{t-2}$)	0.8165 [0.9498]	0.8796 *[0.6329]*	0.8260	0.7310 [0.9293]	0.8066 *[0.4494]*	0.7165	-0.0642 [0.3970]	0.5144 *[0.3039]*	0.1698
corr($\Delta_4 p_t$, $\Delta_4 m_{t-3}$)	0.8509 [0.8776]	0.8684 *[0.7686]*	0.8259	0.7687 [0.7576]	0.8148 *[0.5131]*	0.7152	-0.0271 [0.5100]	0.5246 *[0.3284]*	0.1743
corr($\Delta_4 p_t$, $\Delta_4 m_{t-4}$)	0.8773 *[0.6712]*	0.8503 [0.8290]	0.8237	0.7998 [0.5044]	0.8155 *[0.4123]*	0.7088	0.2223 [0.6112]	0.5370 *[0.1741]*	0.0809
corr($\Delta_4 p_t$, $\Delta_4 m_{t+1}$)	0.7088 [0.8490]	0.7974 *[0.7027]*	0.7446	0.6208 *[0.7089]*	0.7211 [0.8340]	0.6896	-0.5282 [0.7811]	0.0293 *[0.1916]*	-0.4434
corr($\Delta_4 p_t$, $\Delta_4 a_t$)	-0.2752 [0.7701]	-0.2230 *[0.5514]*	-0.3255	-0.3288 [0.4891]	-0.3039 *[0.2623]*	-0.4494	-0.3401 [0.6927]	-0.2986 *[0.6490]*	-0.4590
corr($\Delta_4 p_t$, $\Delta_4 a_{t-1}$)	-0.2960 [0.8391]	-0.2308 *[0.5507]*	-0.3305	-0.3880 [0.5691]	-0.3466 *[0.2697]*	-0.4760	-0.1467 *[0.8756]*	-0.1456 [0.9031]	-0.1076
corr($\Delta_4 p_t$, $\Delta_4 a_{t-2}$)	-0.3085 [0.9239]	-0.2327 *[0.5911]*	-0.3253	-0.3883 [0.5372]	-0.3638 *[0.3613]*	-0.4780	0.2255 [0.5611]	-0.2985 *[0.2056]*	0.0874
corr($\Delta_4 p_t$, $\Delta_4 a_{t-3}$)	-0.3073 [0.9845]	-0.2343 *[0.7130]*	-0.3035	-0.3645 [0.9314]	-0.3342 *[0.7690]*	-0.3774	0.3535 *[0.1338]*	-0.4161 [0.2515]	-0.0398
corr($\Delta_4 p_t$, $\Delta_4 a_{t-4}$)	-0.2945 [0.9391]	-0.2391 *[0.8122]*	-0.2808	-0.3788 *[0.5299]*	-0.3329 [0.8057]	-0.2975	-0.2995 [0.5698]	-0.3560 *[0.5287]*	-0.1492
corr($\Delta_4 p_t$, $\Delta_4 a_{t+1}$)	-0.2598 [0.6346]	-0.2420 *[0.5663]*	-0.3393	-0.3037 [0.5847]	-0.3006 *[0.4643]*	-0.4044	-0.3150* *[0.0837]*	-0.3419 [0.1791]	-0.8024

	Finland			Norway		
	S.I.	S.P.	data	S.I.	S.P.	data
S.D.($\Delta_4 p_t$)	0.1051*** *[0.0000]*	0.0593*** [0.0070]	0.0248	0.0237 *[0.6135]*	0.0226 [0.7235]	0.0205
corr($\Delta_4 p_t$, $\Delta_4 p_{t-1}$)	0.9226 *[0.4722]*	0.9972 [0.7201]	0.9771	0.9865 *[0.2928]*	0.9820 [0.3432]	0.9242
corr($\Delta_4 p_t$, $\Delta_4 p_{t-2}$)	0.8712 *[0.6005]*	0.9906 [0.6680]	0.9424	0.9474 *[0.3867]*	0.9358 [0.4782]	0.8483
corr($\Delta_4 p_t$, $\Delta_4 p_{t-3}$)	0.9233 [0.9308]	0.9815 *[0.6685]*	0.9085	0.8854 *[0.4800]*	0.8720 [0.5720]	0.7643
corr($\Delta_4 p_t$, $\Delta_4 p_{t-4}$)	0.9765 *[0.4263]*	0.9714 [0.5168]	0.8776	0.8063 *[0.4702]*	0.8026 [0.5780]	0.6976
corr($\Delta_4 p_t$, $\Delta_4 p_{t-5}$)	0.9121 [0.6942]	0.9619 *[0.5131]*	0.8582	0.7176 [0.9240]	0.7383 *[0.8633]*	0.7010
corr($\Delta_4 p_t$, $\Delta_4 m_t$)	0.4593 [0.9809]	0.6394 *[0.2854]*	0.4640	0.0620 [0.9374]	0.3238 *[0.2639]*	0.0806
corr($\Delta_4 p_t$, $\Delta_4 m_{t-1}$)	0.4970 [0.9263]	0.6804 *[0.2860]*	0.5154	0.1844 [0.7087]	0.4627* *[0.0649]*	0.1016
corr($\Delta_4 p_t$, $\Delta_4 m_{t-2}$)	0.5549 [0.9646]	0.7145 *[0.3816]*	0.5643	0.2811 [0.3901]	0.5282** *[0.0264]*	0.0928
corr($\Delta_4 p_t$, $\Delta_4 m_{t-3}$)	0.5788 [0.9937]	0.7146 *[0.5119]*	0.5806	0.3694 [0.2329]	0.5401** *[0.0402]*	0.0899
corr($\Delta_4 p_t$, $\Delta_4 m_{t-4}$)	0.6219 [0.9324]	0.7157 *[0.5389]*	0.6045	0.4341 [0.0691]	0.5008** *[0.0259]*	0.0540
corr($\Delta_4 p_t$, $\Delta_4 m_{t+1}$)	0.4405 [0.8554]	0.5892 *[0.3034]*	0.4039	-0.0496 [0.9436]	0.1445 *[0.4168]*	-0.0333
corr($\Delta_4 p_t$, $\Delta_4 a_t$)	-0.1262 [0.8168]	-0.0000 *[0.3351]*	-0.1681	-0.5013 *[0.1179]*	-0.4413 [0.1410]	-0.1542
corr($\Delta_4 p_t$, $\Delta_4 a_{t-1}$)	-0.1270 [0.9505]	0.0324 *[0.3912]*	-0.1163	-0.5044 [0.0797]	-0.4423* *[0.0783]*	-0.1579
corr($\Delta_4 p_t$, $\Delta_4 a_{t-2}$)	-0.0932 [0.8305]	0.0677 *[0.4910]*	-0.0561	-0.4720 *[0.1017]*	-0.3934 [0.1469]	-0.1653
corr($\Delta_4 p_t$, $\Delta_4 a_{t-3}$)	-0.1381 [0.7201]	0.0337 *[0.5992]*	-0.0705	-0.4218* *[0.0962]*	-0.3391 [0.1779]	-0.1025
corr($\Delta_4 p_t$, $\Delta_4 a_{t-4}$)	-0.1216 *[0.6538]*	0.0276 [0.6848]	-0.0460	-0.3789** *[0.0387]*	-0.2920 [0.1091]	-0.0389
corr($\Delta_4 p_t$, $\Delta_4 a_{t+1}$)	-0.0826 [0.6295]	-0.0189 *[0.3435]*	-0.1636	-0.4919* *[0.0701]*	-0.4518* [0.0785]	-0.0994

Table 5 continued.

lead us to the conclusion that the empirical co-movement of inflation and demand is matched clearly better by the sticky-information Phillips curve.

The third group of moments along which we compare the two Phillips curves are moments that describe the co-movement of inflation and supply. In this domain, both models perform rather similarly. Sticky prices matches only a narrow majority (53%) of moments more closely (see column "co-movements to supply" in Table 4). Across countries, no clear winner with regard to correlations between inflation and supply arises with sticky information matching a majority of moments more closely in four (US, Japan, France, Canada) of the eleven countries and is beaten five times (UK, Italy, Sweden, Finland, Norway). To summarize, sticky prices describes the response of inflation to supply slightly better than sticky information but the relative model performance is not as unambiguous as in the other two groups of moments.

5 Conclusion

This paper has provided an empirical cross-country comparison of the sticky-price and sticky-information Phillips curves on the basis of second moments of inflation. The analysis revealed a strong systematic pattern in model performance by moment type. Sticky prices are more successful in matching unconditional moments of inflation while it is the strength of sticky information to match demand reactions of inflation.

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