RUHR
ECONOMIC PAPERS

Christian Bredemeier
Henry Goecke

Sticky Prices vs. Sticky Information

A Cross-Country Study of Inflation Dynamics

Ruhr Graduate School in Economics
technische universität dortmund

#255

Imprint

Ruhr Economic Papers

Published by

Ruhr-Universität Bochum (RUB), Department of Economics
Universitätsstr. 150, 44801 Bochum, Germany

Technische Universität Dortmund, Department of Economic and Social Sciences
Vogelpothsweg 87, 44227 Dortmund, Germany

Universität Duisburg-Essen, Department of Economics
Universitätsstr. 12, 45117 Essen, Germany

Rheinisch-Westfälisches Institut für Wirtschaftsforschung (RWI)
Hohenzollernstr. 1-3, 45128 Essen, Germany

Editors

Prof. Dr. Thomas K. Bauer
RUB, Department of Economics, Empirical Economics
Phone: +49 (0) 234/3 22 83 41, e-mail: thomas.bauer@rub.de

Prof. Dr. Wolfgang Leininger
Technische Universität Dortmund, Department of Economic and Social Sciences
Economics – Microeconomics
Phone: +49 (0) 231/7 55-3297, email: W.Leininger@wiso.uni-dortmund.de

Prof. Dr. Volker Clausen
University of Duisburg-Essen, Department of Economics
International Economics
Phone: +49 (0) 201/1 83-3655, e-mail: vclausen@vwl.uni-due.de

Prof. Dr. Christoph M. Schmidt
RWI, Phone: +49 (0) 201/81 49-227, e-mail: christoph.schmidt@rwi-essen.de

Editorial Office

Joachim Schmidt
RWI, Phone: +49 (0) 201/81 49-292, e-mail: joachim.schmidt@rwi-essen.de

Ruhr Economic Papers #255

Responsible Editor: Wolfgang Leininger

ISSN 1864-4872 (online) – ISBN 978-3-86788-297-2

Ruhr Economic Papers #255

Christian Bredemeier and Henry Goecke

Sticky Prices vs. Sticky Information

A Cross-Country Study of Inflation Dynamics

Ruhr Graduate School in Economics

technische universität dortmund

Bibliografische Informationen der Deutschen Nationalbibliothek

Die Deutsche Bibliothek verzeichnet diese Publikation in der deutschen Nationalbibliografie; detaillierte bibliografische Daten sind im Internet über: *http://dnb.d-nb.de* abrufbar.

ISSN 1864-4872 (online)
ISBN 978-3-86788-297-2

Christian Bredemeier and Henry Goecke[1]

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

Abstract

This paper empirically compares sticky-price and sticky-information Phillips curves considering inflation dynamics in six countries (US, UK, Germany, France, Canada, and Japan). We evaluate the models' abilities to match empirical second moments of inflation. Under baseline calibrations, the two models perform similarly in almost all countries. Under estimated parametrizations, sticky information performs better in France while sticky prices dominate in the UK and Germany. Sticky prices match unconditional moments of inflation dynamics better while sticky information is more successful in matching co-movement of inflation with demand. Both models' performances worsen where inflation dynamics differ from the US benchmark.

JEL Classification: E31, E32, E37

Keywords: Phillips curve; sticky information; sticky prices

April 2011

---

1 Christian Bredemeier, TU Dortmund University and Ruhr Graduate School in Economics; Henry Goecke, TU Dortmund University. *– We would like to thank Oliver Coibion, Falko Juessen, Ludger Linnemann, Rolf Scheufele, and Fabien Tripier for helpful comments and suggestions. The paper has benefitted from conference participants at the 2011 Conference of the Royal Economic Society, the 2010 Annual Congress of the European Economic Association, the 2010 Annual Congress of Verein für Socialpolitik, the 2010 Spring Meeting of Young Economists, the 2010 Annual Conference of the Scottish Economic Society, the 2010 Conference Theories and Methods in Macroeconomics, the Workshop Heterogeneous Nations and Globalized Financial Markets: New Challenges for Central Banks, the DIW Macroeconometric Workshop 2010, and the 2010 Doctoral Conference of the Ruhr Graduate School in Economics.* *– All correspondence to Henry Goecke, TU Dortmund University, Dept. of Economics, Applied Economics, Vogelpothsweg 87, 44227 Dortmund, Germany, E-Mail: henry.goecke@tu-dortmund.de.*

1 Introduction

Mankiw and Reis (2002) proposed sticky information as an alternative to the workhorse of monetary analysis, the sticky-price approach. The basic idea of sticky information is that information spreads slowly through the economy. Mankiw and Reis argue that this approach is favorable to the sticky-price approach because it is able to predict certain empirical observations that can not be generated by sticky prices: hump-shaped responses of inflation to monetary impulses, contractionary disinflations, and the acceleration phenomenon.

Reis (2006) examines the second-moment performance of the sticky-information Phillips curve in the otherwise simple Mankiw and Reis (2002) model. In this model, the sticky-information Phillips curve represents the monetary side of the economy, while the model is closed by exogenous stochastic processes on the real side. Reis finds that even such a simple sticky-information model matches selected second moments of US inflation reasonably well.

In this paper, we examine whether the finding of Reis is unique to a sticky-information model or whether it can also be achieved using a sticky-price model. We contribute to the literature on the horse race between sticky information and sticky prices methodologically in several respects. While certain previous studies have focussed on selected properties (e.g. Korenok and Swanson 2007, Korenok 2008, Abbott 2010), we take a broader look on inflation dynamics and consider inflation variance and persistence as well as its relation to dynamics in demand and supply. Considering only some properties of the inflation process may be misleading as we find that improving a model's fit to e.g. inflation persistence worsens its ability to predict e.g. responses to demand shocks.

Furthermore we do not only consider US inflation dynamics, but also those in five more countries, the UK, Germany, France, Canada, and Japan. Our motivation to take this cross-country perspective is to test whether relative model performances are country-specific. We find that some moments which are important for the identification of our two models (predominantly inflation persistence and its reaction to demand innovations) differ substantially across countries. It is therefore interesting to evaluate how the models cope with these differences. The unique cross-country perspective further distinguishes our study from the existing literature on the horse race between sticky information and sticky prices.

Finally, we compare the model performances both in moment-based and likelihood evaluations. Considering the models from both points of view reveals the interesting fact that, in many cases, one model is supported in the moment-based evaluation and the other in the likelihood-based comparison. Relying on only one perspective may therefore be misleading.

We compare the two Phillips curves in the framework of the Mankiw-Reis model which allows a comparison on a leveled playing field. For a fair comparison, the two Phillips curves should be applied in models which are otherwise identical. Furthermore, the estimation of the rest of the model should be separable from the estimation of the Phillips curve. Otherwise, parameter estimates for the other equations would be influenced by the specific Phillips curve chosen. The Mankiw-Reis model fulfills these criteria. When we estimate the models, we make use of the separability of the model and first estimate the real side of the economy and then the Phillips curves. This ensures that, when comparing models, both have not only the same equations but also the same parameter estimates on the real side of the economy and are exposed to the same sequence of shocks.[1]

Although the Mankiw-Reis model is very stylized in the way the model is closed, it seems sophisticated enough to capture inflation dynamics well. In our empirical analysis, we can reject equality between models generated by the estimated models and empirical moments at 99% significance in only 2% 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 innova-

[1]These features distinguish our work from most previous studies comparing Phillips curves empirically. For more details on previous comparisons of sticky prices and sticky information, see the literature overview at the end of this section.

tions in these variables. For a set of selected second moments of inflation, we generate distributions of model moments by repeated simulations of the models.

We compare the empirical performance of the two models on the ground of the absolute difference between model moments and empirical moments, the number of moments for which equality of empirical and model moment can be rejected, and the likelihoods of the two models given the empirical moments. We perform two comparisons of sticky prices and sticky information. In the first comparison, we regard calibrated versions of the two models, whereas we consider estimated models in the second comparison.

Our results do not clearly support one of the two competing models. In the baseline calibration, the models perform similarly in the US, Germany, France, Canada, and Japan. Only in the UK, sticky information is clearly supported by the data. Under the estimated parametrization, sticky prices perform slightly better in the UK and Germany, while sticky information is supported by French data, and both models perform similarly in the US, Canada, and Japan.

The unique cross-country perspective of our study furthermore reveals that both models systematically generate very smooth inflation and have difficulties in countries where inflation persistence is relatively low compared to the US. A similar result is found with respect to cross-correlations which empirically differ from the US observations. The finding of a country-dependend model performance is a new insight as no previous study in the literature has compared sticky information and sticky prices in a cross-country perspective.

Our broad view on the inflation process reveals that sticky prices perform rather well in matching unconditional moments of the inflation process, while being less successful with inflation reactions to changes in demand. For sticky information, we observe a trade-off in the empirical fit. Calibrations which are successful in generating empirical cross-correlations of inflation with supply and demand have a worse fit in unconditional moments and vice versa.

To sum up our results, the overall empirical performance allows no clear distinction between the two concepts. However, if one is predominantly interested in matching unconditional moments of inflation dynamics, sticky prices should be used. Researchers who focus on co-movement of inflation with demand may obtain better results applying sticky information. These results rely on our cross-country perspective since, in the US, model performances are almost identical.

A number of previous papers have compared sticky prices and sticky information empirically for one specific economy. In line with our results, evidence from the literature is also mixed and does not clearly favor one of the models.

In this literature, Mankiw and Reis (2002), Kiley (2007), and Korenok (2008) work with similar model approaches than we do, but these studies are different from ours in other respects. Mankiw and Reis (2002) consider impulse responses of inflation qualitatively. They conclude that sticky information matches the shape of observed impulse responses better than sticky prices. Our study evaluates the empirical performance quantitatively and also targets unconditional moments of inflation dynamics.

Similarly to the Mankiw-Reis model, Kiley (2007) works in models which consist of a Phillips curve and reduced-form equations for the rest of the economy. His evaluations are based on the predictive power of the different Phillips curves for inflation where expectations that enter the Phillips curves are obtained from a reduced-form system for marginal cost. By contrast, we approach the inflation process in a broader way also considering higher moments of inflation and use model-consistent rational expectations. In the results of Kiley (2007), the sticky-price model fits better than the sticky information model.

A modeling strategy similar to ours is used by Korenok (2008) who determines the rational-expectations solution in a model which consists of a Phillips curve and an exogenous stochastic process for unit labor costs. His analysis differs from ours in the estimation method and the focus of the model evaluation. Korenok (2008) uses a Bayesian full information likelihood approach and estimates both sides of the model jointly whereas we apply a two-step procedure. The model evaluation of Korenok (2008) is based on a likelihood evaluation in a bivariate model with inflation and unit labor costs, while we also distinguish between the relations to demand and supply, respectively. The results of Korenok (2008) favor the sticky-price model.

Opposed to our closed-form expectations approach, Coibion (2010), Ciobîcă (2010), and Dupor, Kitamura, and Tsuruga (2010) perform single equation evaluations of the competing Phillips curves determining the expectation terms outside the model. Coibion (2010) estimates different Phillips curves with US data using instruments for the output gap and expectations determined from VARs or survey data, respectively. He performs two regression-based tests to compare the competing Phillips curves. In his results, the sticky information Phillips curve is statistically dominated by the new Keynesian Phillips curve. Ciobîcă (2010) basically repeats the analysis of Coibion (2010) with Romanian data and comes to the same conclusion. Dupor et al. (2010) compare sticky prices and sticky information in a nested model and obtain predicted series of a real marginal cost measure and inflation from a VAR. They, too, find that sticky prices dominate sticky information empirically.

A third 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, López-Salido, and Nelson (2005) use a model without capital accumulation which, next to the Phillips curve, encompasses an IS relation and equations for money demand and money growth. They estimate the model using Maximum Likelihood for US data. In their estimation results, sticky information has the higher likelihood.

Korenok and Swanson (2007) use a calibrated DSGE model with different Phillips curves. They base their model evaluation on impulse response analyses and on evaluating the joint distribution of inflation and the output gap. They find that, for a standard level of stickiness, the sticky-information model performs better than the standard sticky-price model.

Abbott (2010) uses the same model as Korenok and Swanson (2007) and focuses on the reaction of inflation to monetary innovations. The results confirm the results of Korenok and Swanson (2007) and also support sticky information relative to the standard sticky price model.

Paustian and Pytlarczyk (2006) consider sticky-price and sticky-information variants of the Smets and Wouters (2003) DSGE model which they estimate with Bayesian techniques for the Euro Area. Based on the posterior odds ratio, they conclude that the sticky-price model dominates the sticky-information model.

Laforte (2007) considers sticky-price and sticky-information pricing in a smaller DSGE model which he estimates with Bayesian techniques for US data. In his results, sticky information has the higher posterior odds than sticky prices.

Some studies also allow for lags of inflation in the Phillips curves. It can be summarized as a general result, that, when allowing for lags, a sticky-price Phillips curve with sufficiently many lags of inflation fits best (see e.g. Kiley 2007, Korenok and Swanson 2007, and Abbott 2010) although there is often no sticky-information Phillips curve with backward-looking parts included in the comparisons. 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.

The remainder of the paper is organized as follows. Section 2 presents models and our empirical strategy. The results of the analysis can be found in Section 3. Finally, Section 4 concludes.

2 Models and Empirical Strategy

2.1 Models

Phillips curves. We compare the concepts of sticky information and sticky prices which result in different Phillips curves. For the following empirical analysis, we use only the two Phillips curves and close the models identically in the simple way proposed by 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.[2] 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 because this 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. A Phillips curve represents 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 regarding m_t and a_t: We assume that these variables are exogenous to inflation and

[2]This particular form of the Phillips curve results from the sticky-price model used in Mankiw and Reis (2002). Similarly, the following sticky-information Phillips curve stems from the same paper.

that they follow independent stochastic processes.

While Reis (2006) finds that first-order auto-regressive processes are sufficient for quarterly US data, processes of higher order describe the growth rates of nominal income and productivity in other countries more adequately. We therefore allow the growth rates Δa_t and Δm_t to follow auto-regressive processes of up to order eight. Given such processes, we write Δm_t and Δa_t as a moving average of past shocks,

$$\Delta a_t = \sum_{i=0}^{\infty} \omega_i \varepsilon_{t-i}^{a} \tag{3}$$

and

$$\Delta m_t = \sum_{i=0}^{\infty} \chi_i \varepsilon_{t-i}^{m}. \tag{4}$$

While assuming that productivity follows an exogenous stochastic process as in (3) is standard in the literature, assuming this also for nominal income is rather unusual. Mankiw and Reis (2011) justify this assumption by describing how monetary policy can ensure that nominal income follows such a process. Throughout the model, we will refer to Δm and Δa as changes in demand and supply, respectively.

Modeling the dynamics of nominal income and productivity in this way implies ignoring any structural relationships governing these dynamics. However, estimating (4) captures any structure in the data which does not include feedback from inflation to nominal income. Structural relations that are missed by the assumptions (3) and (4) are missed in both models equally. 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. The Mankiw-Reis model seems sophisticated enough to capture inflation dynamics well. In our empirical analysis, we can reject equality between models generated by the estimated models and empirical moments at 99% significance in only 2% 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 nominal income and productivity growth described above. Shocks to Δm_t and Δa_t are thus the only driving forces for dynamics in the models. The solution for inflation is a moving average of past shocks to nominal income and productivity,

$$\pi_t = \sum_{i=0}^{\infty} \gamma_i^z \varepsilon_{t-i}^m + \sum_{i=0}^{\infty} \xi_i^z \varepsilon_{t-i}^a, \tag{5}$$

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, see Appendix A.1.

2.2 Empirical Strategy

Our first empirical analysis starts from the empirical exercise reported in Reis (2006). He considers the Mankiw and Reis (2002) model with sticky information, i.e. the model consists of equations (2), (3), and (4) where the parameters in (3) are such that the process is white noise and (4) is AR(1). He determines a sequence of model-predicted inflation rates by combining the estimated empirical innovations to nominal income and productivity with the MA coefficients of inflation (5) for a chosen parametrization $\alpha = 0.11$ and $\lambda = 0.25$. He calculates the second moments of this sequence and compares them to the empirically observed counterparts. His informal judgement about the accuracy of the model is based on the absolute differences between empirical and model moments.

The quantitative analysis of Reis is augmented in several respects in this paper. First, we consider five more countries, the UK, Germany, France, Canada, and Japan. Second, we also consider a sticky-price Phillips curve and compare the two concepts. We third extend the analysis methodologically by comparing not only absolute deviations between model moments and empirical observations but also evaluating the statistical properties of these differences. We generate a distribution of model moments by repeated simulation. Using this distribution, we perform a t-test of significant difference to the empirical moments for each model moment. Furthermore, we evaluate the likelihoods of the two models as the joint density of the empirical moments in the joint distribution of model moments. We determine the probability distribution of the empirical moments by a bootstrapping method.

In the empirical analysis, we simulate the model on a quarterly basis as described in the previous section but evaluate the dynamics of annual changes, i.e. we target the dynamics of $\Delta_4 p_t = p_t - p_{t-4}$.[3] The reason to use annual changes lies in potential measurement errors in quarterly seasonally adjusted data which are extenuated by considering annual changes. 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. For example, the autocorrelation of quarterly inflation in Japan is only one third of the US value, while the autocorrelation of annual inflation rates is almost the same in the two countries. Inflation persistence is an important moment for the identification of the models which systematically predict very smooth inflation. We therefore want to avoid measurement error in this important moment and use annual changes.

As Reis (2006), we take a broad perspective on the inflation process. Our set of considered moments therefore includes unconditional moments of inflation dynamics (standard deviation and autocorrelation) as well as measures of the co-movements with supply and demand (cross-correlation with leads and lags of nominal income and labor productivity).

In order to relate our results to those of Reis (2006), we use the same data and sample period in the case of the US. For comparability to Reis (2006), we also start with a given benchmark parametrization, $\alpha = 0.11$ and $\lambda = 0.25$. Later on, we also estimate α and λ for each model and country using the method of simulated moments (Davidson and MacKinnon 2004, Chapter 7). We then repeat the comparison of the two models under the estimated parametrization. A detailed description of our empirical strategy

[3] Throughout the paper, we use Δ_4 as $1 - L^4$ where L is the lag operator.

can be found in Appendix A.2. The appendix also contains the results of a Monte Carlo study in which we check the reliability of the estimation procedure.

In our analysis, we use quarterly data on nominal income, labor productivity, and consumer price indices. Most of our data stems from the OECD and the respective national statistical offices. Data sources and details are described in Appendix A.3.

3 Results

Our empirical analysis starts with an estimation of the auto-regressive processes for nominal income and productivity growth for the six countries in our sample. In 7 of the 12 cases, higher-order processes are needed to describe the dynamics in productivity and nominal income growth in the various countries. The estimated auto-regressive processes are reported in Appendix A.4.

3.1 Results under Baseline Calibration

Table 1 presents the results of the model comparison under the baseline parametrization. For each country and moment, the following information is reported in the table: the first line in each cell presents the two moments predicted by the sticky-information model (S.I.) and the sticky-price model (S.P.) as well as the observed value from the data. The numbers reported in round brackets are the standard deviations of the respective model moments. The numbers in square brackets represent the p-values of a test of equality between the respective model moment and the empirical counterpart.

We evaluate the empirical performance of the models by different measures which can be found at the bottom of the table. The first measure is the number of moments which are closer to the empirical moment in absolute terms than the moment of the competing model. We then count the moments for which we can reject that they are equal to the empirical moment at the 5% level. The third measure of performance is the model's likelihood given the empirical moments, $\Pi_{x \in X} f(x)$. Since this joint density is in general a very small number, the table reports the common logarithm.

First, the results confirm our view that the Mankiw-Reis model is sufficiently sophisticated for our analysis. The models match most considered moments well with not more than two (out of 16) rejected moments per country in the US, Germany, France, and Japan. From the six rejected moments in Canada, only two are also rejected at the 1% significance level. Although the models are less successful in matching UK inflation dynamics, we regard the overall performances as sufficiently good to draw conclusions from these results. We now compare the two models' performances country by country.

For the US, absolute deviations between model and empirical moments are small. A similar results is also observed by Reis (2006) who considers quarterly inflation and finds that, with the exception of the autocorrelation, predictions of the sticky-information model do not differ from the empirical counterpart by much. Focussing on annual inflation, we find that this result also holds for the autocorrelation of inflation. However, this finding is not unique to the sticky information model, the sticky-price model performs similarly.

Considering only absolute differences does not exploit the statistical properties of the moments. For this reason, we also present standard deviations as well as p-values of a t-test of significant difference between the respective model moment and the empirical counterpart. The results confirm Reis' judgement that the sticky-information model fits the data remarkably well. No model moment is significantly different from the data moments at the 5% level. But models perform similarly again with no rejected moment also for sticky prices.

Comparing the two competing models for the US, sticky prices perform slightly better than sticky information. The number of moments closer to the data is equal for both models and, in both models, no moment is rejected. Considering the models' likelihoods, sticky prices perform slightly better than sticky information.

	United States			United Kingdom			Germany		
	S.I.	S.P.	data	S.I.	S.P.	data	S.I.	S.P.	data
S.D.($\Delta_4 p_t$)	0.0228	0.0213	0.0235	0.0104	0.0080	0.0500	0.0316	0.0242	0.0158
	(0.0028)	(0.0023)	(0.0023)	(0.0025)	(0.0021)	(0.0063)	(0.0084)	(0.0069)	(0.0016)
	[0.8382]	[0.4880]		[0.0000]	[0.0000]		[0.0640]	[0.2345]	
Corr($\Delta_4 p_t, \Delta_4 p_{t-1}$)	0.9968	0.9959	0.9864	0.9838	0.9818	0.9738	0.9951	0.9943	0.9503
	(0.0042)	(0.0123)	(0.0436)	(0.0049)	(0.0101)	(0.0435)	(0.0057)	(0.0102)	(0.0507)
	[0.8122]	[0.8326]		[0.8199]	[0.8578]		[0.3792]	[0.3949]	
Corr($\Delta_4 p_t, \Delta_4 m_t$)	0.5258	0.5647	0.5883	-0.1048	0.1420	-0.4391	0.6150	0.7249	0.4460
	(0.1454)	(0.1096)	(0.0719)	(0.1471)	(0.1167)	(0.1047)	(0.1948)	(0.1017)	(0.0867)
	[0.6999]	[0.8570]		[0.0641]	[0.0002]		[0.4281]	[0.0369]	
Corr($\Delta_4 p_t, \Delta_4 m_{t-1}$)	0.5633	0.6250	0.6167	0.0082	0.2761	-0.4012	0.6521	0.7406	0.5254
	(0.1324)	(0.0938)	(0.0673)	(0.1366)	(0.1000)	(0.0928)	(0.1730)	(0.0756)	(0.0807)
	[0.7191]	[0.9424]		[0.0132]	[0.0000]		[0.5070]	[0.0519]	
Corr($\Delta_4 p_t, \Delta_4 m_{t+1}$)	0.4960	0.5151	0.5523	-0.1993	-0.0036	-0.4416	0.5856	0.6939	0.3775
	(0.1557)	(0.1281)	(0.0721)	(0.1536)	(0.1337)	(0.0871)	(0.2095)	(0.1321)	(0.0800)
	[0.7428]	[0.8005]		[0.1699]	[0.0061]		[0.3532]	[0.0404]	
Corr($\Delta_4 p_t, \Delta_4 a_t$)	-0.4026	-0.4721	-0.4310	-0.4784	-0.4379	-0.2325	-0.1777	-0.1840	-0.0059
	(0.1444)	(0.1339)	(0.1001)	(0.1387)	(0.1234)	(0.1302)	(0.1796)	(0.1777)	(0.1348)
	[0.8716]	[0.8059]		[0.1961]	[0.2523]		[0.4444]	[0.4248]	
Corr($\Delta_4 p_t, \Delta_4 a_{t-1}$)	-0.4162	-0.4675	-0.4312	-0.4981	-0.4075	-0.2462	-0.2376	-0.2237	-0.0060
	(0.1407)	(0.1261)	(0.0867)	(0.1325)	(0.1122)	(0.1026)	(0.1801)	(0.1771)	(0.1098)
	[0.9273]	[0.8126]		[0.1329]	[0.2888]		[0.2722]	[0.2959]	
Corr($\Delta_4 p_t, \Delta_4 a_{t+1}$)	-0.3890	-0.4627	-0.4176	-0.4427	-0.4644	-0.1851	-0.1492	-0.1723	-0.0549
	(0.1471)	(0.1414)	(0.0878)	(0.1434)	(0.1336)	(0.1035)	(0.1806)	(0.1796)	(0.1070)
	[0.8675]	[0.7863]		[0.1452]	[0.0984]		[0.6532]	[0.5742]	
moments closer to data	4	4		5	3		5	3	
moments rejected at 5%	0	0		2	4		0	2	
$\log_{10} \Pi_{x \in X} f(x)$	5.31	6.43		-52.80	-96.95		-9.86	-3.44	

Table 1: Second moments of inflation as predicted by models and in data.

	France			Canada			Japan		
	S.I.	S.P.	data	S.I.	S.P.	data	S.I.	S.P.	data
S.D.$(\Delta_4 p_t)$	0.1726	0.0344	0.0109	0.0139	0.0141	0.0138	0.0967	0.0233	0.0221
	(0.0104)	(0.0081)	(0.0056)	(0.0028)	(0.0031)	(0.0039)	(0.0239)	(0.0161)	(0.0088)
	[0.0000]	[0.0165]		[0.9945]	[0.9626]		[0.0034]	[0.9450]	
Corr$(\Delta_4 p_t, \Delta_4 p_{t-1})$	0.9999	0.9964	0.9253	0.9920	0.9942	0.8686	0.9983	0.9826	0.9592
	(0.0002)	(0.0062)	(0.0568)	(0.0123)	(0.0107)	(0.0657)	(0.0028)	(0.0090)	(0.0510)
	[0.1887]	[0.2130]		[0.0647]	[0.0590]		[0.4435]	[0.6506]	
Corr$(\Delta_4 p_t, \Delta_4 m_t)$	0.6480	0.7904	0.4693	0.2403	0.1838	-0.4161	0.6556	0.6298	0.7598
	(0.3696)	(0.2608)	(0.0469)	(0.1785)	(0.1915)	(0.2329)	(0.3176)	(0.1791)	(0.0326)
	[0.6314]	[0.2257]		[0.0253]	[0.0467]		[0.7442]	[0.4754]	
Corr$(\Delta_4 p_t, \Delta_4 m_{t-1})$	0.6602	0.7975	0.4743	0.3392	0.2426	-0.3099	0.6640	0.6395	0.7806
	(0.3709)	(0.2405)	(0.0671)	(0.1776)	(0.1812)	(0.1725)	(0.3094)	(0.1454)	(0.0629)
	[0.6220]	[0.1957]		[0.0088]	[0.0272]		[0.7119]	[0.3731]	
Corr$(\Delta_4 p_t, \Delta_4 m_{t+1})$	0.6585	0.7669	0.4500	0.0962	0.0388	-0.5437	0.6375	0.5867	0.7382
	(0.3723)	(0.2766)	(0.0678)	(0.1784)	(0.1998)	(0.1707)	(0.3218)	(0.1986)	(0.0560)
	[0.5816]	[0.2657]		[0.0096]	[0.0267]		[0.7580]	[0.4631]	
Corr$(\Delta_4 p_t, \Delta_4 a_t)$	0.3777	0.4747	0.2626	-0.1079	-0.1307	-0.3398	0.1321	0.0175	0.0903
	(0.2465)	(0.2294)	(0.1427)	(0.1929)	(0.1980)	(0.1686)	(0.1789)	(0.1595)	(0.2201)
	[0.6861]	[0.4323]		[0.3655]	[0.4215]		[0.8827]	[0.7888]	
Corr$(\Delta_4 p_t, \Delta_4 a_{t-1})$	0.3803	0.4812	0.2499	-0.0733	-0.1199	-0.3384	0.0976	0.0209	0.1708
	(0.2476)	(0.2329)	(0.1212)	(0.1924)	(0.1923)	(0.1281)	(0.1793)	(0.1683)	(0.1589)
	[0.6360]	[0.3783]		[0.2515]	[0.3443]		[0.7599]	[0.5173]	
Corr$(\Delta_4 p_t, \Delta_4 a_{t+1})$	0.4047	0.4530	0.2753	-0.1300	-0.1489	-0.3264	0.1341	0.0186	-0.0221
	(0.2475)	(0.2305)	(0.1179)	(0.1957)	(0.2050)	(0.1421)	(0.1786)	(0.1521)	(0.1695)
	[0.6371]	[0.4926]		[0.4167]	[0.4765]		[0.5257]	[0.8579]	
moments closer to data	6	2		2	6		5	3	
moments rejected at 5%	1	1		3	3		1	0	
$\log_{10} \Pi_{x \in X} f(x)$	-323.00	-27.43		-25.69	-31.28		-41.08	3.16	

Table 1 continued.

For the UK, the sticky-information model performs better than the sticky-price model. The sticky-information model produces moments that are closer to the data in five out of eight cases. For sticky information, two moments are rejected at the 5% level and, for sticky prices, four moments are rejected. As a result of this disability to generate certain data moments, both joint densities are low with sticky information performing better.

For Germany, the results do not allow a clear discrimination between the models. A moments-based evaluation supports sticky information, while sticky prices dominate in a likelihood comparison. The sticky-information model produces five moments that are closer to the data. This finding is confirmed when considering the statistical properties of the moments. For sticky prices, two moments are significantly different from the data moments, while no moment is rejected for sticky information. However, the likelihood is higher for sticky prices than for sticky information in the case of Germany.

A similar picture arises for France. In a moments-based evaluation, sticky information is more successful than sticky prices. The absolute distance to the empirical moments is lower for sticky information in six out of eight cases. For both models, only one moment is rejected. A likelihood comparison, by contrast, supports sticky prices as the likelihood of the sticky-information model is effectively zero. This is driven by the standard deviation of inflation which is strongly rejected for the sticky-information model.

Also for Canada, moments-based evaluation and likelihood comparison show different results. Sticky prices match more moments closer in absolute terms but the number of rejected moments is equal. However, the likelihood is higher for sticky information.

Sticky prices are slightly better in the case of Japan. Sticky information matches more moments closer to the data but has one more rejected moment. Considering the likelihood of the models, sticky prices are supported by Japanese data.

Leaving the country-by-country comparisons of overall model performances, it is also interesting to elicit how the two models perform in situations where moments empirically differ substantially from the US benchmark. One of such moments is the Canadian autocorrelation which is considerably lower than in the other countries. Both models overpredict this moment substantially though equality to the empirical moment can only just not be rejected at 5% significance. Another interesting constellation is given by the negative cross-correlations of inflation to changes in demand in the UK and Canada. In the UK, sticky information can generate two out of three negative signs, while sticky prices are successful in one case. Neither model can generate a negative sign for Canada. Finally, models are more successful with respect to the unusual positive cross-correlations of inflation with changes in supply which are observed in France and Japan. Here, both models predict the signs correctly, while they are also successful in matching the negative relations to supply in the other countries.

All in all, our results do not allow a clear discrimination between the two models. In only one country, we find clear evidence in favor of one model. In the UK, sticky information dominates both in moment and likelihood-based comparisons. Considering the other five countries, evidence is mixed. In moments-based evaluations, sticky information performs better in Germany and France but worse in Canada. For the US and Japan, model performance is similar. In likelihood comparisons, sticky prices perform better in four countries (US, Germany, France, and Japan). The results also show that it is valuable to consider the inflation process broadly. While sticky information is less successful in matching unconditional moments of inflation dynamics (3 vs. 2 rejected moments), it performs better with respect to the inflation reactions to changes in demand (4 vs. 8 rejected moments). The latter finding is in line with Mankiw and Reis (2002) who demonstrated qualitatively that sticky information generates empirically superior inflation responses to demand shocks compared to the sticky-price alternative.

3.2 Estimation Results

This section presents the results from our estimation procedure of the Phillips curve parameters. We estimate the parameters α and λ by matching our two models to the observed second moments of inflation using the method of simulated moments. The results are summarized in Table 2. The table reports

	SI		SP	
	α	λ	α	λ
US	0.2480	0.2604	0.2455	0.2558
	(0.0097)	(0.0070)	(1.8260)	(0.8151)
UK	0.1066	0.0890	0.0019	0.2526
	(0.0966)	(0.0714)	(0.0113)	(0.6056)
Germany	0.2785	0.0105	0.0305	0.2446
	(0.0831)	(0.0022)	(0.0907)	(0.3189)
France	18.2122	0.0325	0.2406	0.2377
	(19.9889)	(0.0355)	(0.9102)	(0.4041)
Canada	3.1487	0.0353	0.0689	0.2377
	(1.3804)	(0.0161)	(0.0447)	(0.0676)
Japan	6.5188	0.0261	0.0394	0.2251
	(1.9556)	(0.0083)	(0.1325)	(0.3388)

Table 2: Estimated values for α and λ from the method of simulated moments estimation.

the point estimates for the parameters α and λ as well as their standard deviations (in brackets) for each country and model.

For the sticky-price model, our estimates for the parameter λ, measuring nominal rigidity, are close to those used in common calibrations ($\lambda \approx 0.25$, e.g. Mankiw and Reis 2002). Concerning real rigidities, measured by α, the estimated values differ substantially across countries. For sticky prices, our estimates lie somewhat above the values discussed in the literature, which range from 0.11 (Reis 2006) to 0.17 (Chari et al. 2000), in two countries, the US and France.[4] The estimates for the other countries are lower.

For the sticky-information model, our results are different. Except for the US, informational rigidities, λ, are lower than those found in the literature (Khan and Zhu 2002; Carroll 2003; Döpke et al. 2008). The estimated real-rigidity parameter α lies very close to the baseline in the UK whereas our estimates are higher for the other five countries. For France, we find a very

[4] In the Mankiw and Reis (2002) version of the two Phillips curves we use, α is a combination of the mark-up power of monopolistic firms θ, the labor-supply elasticity of real wages ψ, and the income elasticity of real wages σ, $\alpha = \frac{\sigma+\psi}{1+\theta\psi}$. Chari, Kehoe, and McGrattan (2000) offer a quantification of these structural parameters which results in the stated value $\alpha = 0.17$.

high point estimate for α which is associated with a very high standard deviation. The problem of an imprecisely estimated degree of real rigidity when both Phillips-curve parameters are estimated jointly is a known phenomenon in the literature (see Khan and Zhu 2002; Döpke et al. 2008).

3.3 Results under Estimated Parametrization

We repeat the model comparison using the estimated parametrization. The results are presented in Table 3. The table is the counterpart to Table 1 and is arranged conformably. Note that the estimation is based on a moment distance such that the moment-based performance tends to improve as compared to the baseline parametrization (at 1% significance, only 2 of the 96 model moments can be rejected). However, we also observe trade-offs in the empirical performances of the models. In particular, sticky information becomes more successful in matching unconditional moments of inflation dynamics when using the estimated parametrization but at the costs of the fit to the empirical cross-correlations. In contrast to the moment-based evaluations, the models' likelihoods are non-targeted measures in the estimation.

The model predicted moments are very similar to those from the baseline parametrization in case of the US. As a consequence, all model evaluations show similar results as under the baseline parametrization. The two competing models perform almost identically.

For the UK, model moments change substantially when using the estimated parameters. Sticky information predicts the standard deviation of inflation substantially better than under the baseline. This however forces the model to perform worse with respect to other moments (the cross-correlation with changes in supply and demand) which results in six rejected moments at the 5% level. This is put into perspective when recognizing that only one of those moments is also rejected at the 1% level (see the reported p-values in the table). The sticky-price model gains with respect to the cross-correlations of inflation with demand and loses concerning other moments. All in all, sticky prices perform slightly better under the estimated parametrizations.

	United States			United Kingdom			Germany		
	S.I.	S.P.	data	S.I.	S.P.	data	S.I.	S.P.	data
S.D.($\Delta_4 p_t$)	0.0240	0.0233	0.0235	0.0477	0.0106	0.0500	0.0188	0.0297	0.0158
	(0.0028)	(0.0025)	(0.0023)	(0.0029)	(0.0019)	(0.0063)	(0.0011)	(0.0075)	(0.0016)
	[0.8926]	[0.9480]		[0.7369]	[0.0000]		[0.1126]	[0.0703]	
Corr($\Delta_4 p_t, \Delta_4 p_{t-1}$)	0.9942	0.9937	0.9864	0.9997	0.9998	0.9738	0.9992	0.9986	0.9503
	(0.0070)	(0.0125)	(0.0436)	(0.0001)	(0.0003)	(0.0435)	(0.0002)	(0.0067)	(0.0507)
	[0.8587]	[0.8711]		[0.5514]	[0.5503]		[0.3349]	[0.3450]	
Corr($\Delta_4 p_t, \Delta_4 m_t$)	0.5566	0.6026	0.5883	0.0348	-0.0328	-0.4391	0.2826	0.6212	0.4460
	(0.1265)	(0.1038)	(0.0719)	(0.1638)	(0.1660)	(0.1047)	(0.2806)	(0.1829)	(0.0867)
	[0.8274]	[0.9099]		[0.0148]	[0.0384]		[0.5781]	[0.3869]	
Corr($\Delta_4 p_t, \Delta_4 m_{t-1}$)	0.6178	0.6726	0.6167	0.0309	-0.0355	-0.4012	0.2709	0.6307	0.5254
	(0.1051)	(0.0848)	(0.0673)	(0.1638)	(0.1649)	(0.0928)	(0.2826)	(0.1642)	(0.0807)
	[0.9929]	[0.6059]		[0.0217]	[0.0532]		[0.3863]	[0.5651]	
Corr($\Delta_4 p_t, \Delta_4 m_{t+1}$)	0.5100	0.5434	0.5523	0.0398	-0.0457	-0.4416	0.2693	0.5967	0.3775
	(0.1451)	(0.1255)	(0.0721)	(0.1646)	(0.1679)	(0.0871)	(0.2811)	(0.2005)	(0.0800)
	[0.7939]	[0.9507]		[0.0097]	[0.0363]		[0.7113]	[0.3098]	
Corr($\Delta_4 p_t, \Delta_4 a_t$)	-0.4752	-0.4973	-0.4310	0.2187	0.1578	-0.2325	0.2523	-0.1147	-0.0059
	(0.1391)	(0.1313)	(0.1001)	(0.1523)	(0.1512)	(0.1302)	(0.1829)	(0.1764)	(0.1348)
	[0.7967]	[0.6880]		[0.0243]	[0.0505]		[0.2558]	[0.6243]	
Corr($\Delta_4 p_t, \Delta_4 a_{t-1}$)	-0.4877	-0.4901	-0.4312	0.2138	0.1457	-0.2462	0.1599	-0.1611	-0.0060
	(0.1320)	(0.1222)	(0.0867)	(0.1525)	(0.1503)	(0.1026)	(0.1835)	(0.1774)	(0.1098)
	[0.7208]	[0.6943]		[0.0123]	[0.0313]		[0.4379]	[0.4571]	
Corr($\Delta_4 p_t, \Delta_4 a_{t+1}$)	-0.4525	-0.4886	-0.4176	0.2430	0.1687	-0.1851	0.2675	-0.1223	-0.0549
	(0.1445)	(0.1397)	(0.0878)	(0.1522)	(0.1521)	(0.1035)	(0.1840)	(0.1781)	(0.1070)
	[0.8365]	[0.6668]		[0.0200]	[0.0544]		[0.1298]	[0.7457]	
moments closer to data	4	4		2	6		3	5	
moments rejected at 5%	0	0		6	4		0	0	
$\log_{10} \Pi_{x \in X} f(x)$	6.42	6.59		-323.00	-323.00		-323.00	-7.27	

Table 3: Model comparison under estimated parametrization.

	France			Canada			Japan		
	S.I.	S.P.	data	S.I.	S.P.	data	S.I.	S.P.	data
S.D.($\Delta_4 p_t$)	0.0273	0.0288	0.0109	0.0215	0.0215	0.0138	0.0380	0.0337	0.0221
	(0.0075)	(0.0076)	(0.0056)	(0.0034)	(0.0034)	(0.0039)	(0.0170)	(0.0169)	(0.0088)
	[0.0773]	[0.0569]		[0.1397]	[0.1354]		[0.4072]	[0.5416]	
Corr($\Delta_4 p_t, \Delta_4 p_{t-1}$)	0.9941	0.9939	0.9253	0.9970	0.9986	0.8686	0.9689	0.9970	0.9592
	(0.0104)	(0.0083)	(0.0568)	(0.0040)	(0.0020)	(0.0657)	(0.0093)	(0.0071)	(0.0510)
	[0.2333]	[0.2319]		[0.0510]	[0.0477]		[0.8510]	[0.4625]	
Corr($\Delta_4 p_t, \Delta_4 m_t$)	0.7924	0.8164	0.4693	0.0626	0.0036	-0.4161	0.5793	0.7704	0.7598
	(0.1965)	(0.2095)	(0.0469)	(0.2237)	(0.2187)	(0.2329)	(0.2246)	(0.2445)	(0.0326)
	[0.1096]	[0.1058]		[0.1383]	[0.1890]		[0.4266]	[0.9657]	
Corr($\Delta_4 p_t, \Delta_4 m_{t-1}$)	0.8366	0.8236	0.4743	0.0956	0.0218	-0.3099	0.6043	0.7773	0.7806
	(0.1714)	(0.1856)	(0.0671)	(0.2191)	(0.2149)	(0.1725)	(0.2042)	(0.2163)	(0.0629)
	[0.0491]	[0.0768]		[0.1460]	[0.2287]		[0.4093]	[0.9885]	
Corr($\Delta_4 p_t, \Delta_4 m_{t+1}$)	0.7506	0.7864	0.4500	-0.0620	-0.1118	-0.5437	0.5488	0.7435	0.7382
	(0.2183)	(0.2296)	(0.0678)	(0.2249)	(0.2215)	(0.1707)	(0.2346)	(0.2593)	(0.0560)
	[0.1884]	[0.1598]		[0.0880]	[0.1225]		[0.4323]	[0.9840]	
Corr($\Delta_4 p_t, \Delta_4 a_t$)	0.3721	0.4658	0.2626	-0.0974	-0.1490	-0.3398	-0.2018	0.1982	0.0903
	(0.2272)	(0.2231)	(0.1427)	(0.2136)	(0.2145)	(0.1686)	(0.1654)	(0.1796)	(0.2201)
	[0.6830]	[0.4430]		[0.3731]	[0.4844]		[0.2888]	[0.7040]	
Corr($\Delta_4 p_t, \Delta_4 a_{t-1}$)	0.4192	0.4735	0.2499	-0.0932	-0.1564	-0.3384	-0.2415	0.1987	0.1708
	(0.2362)	(0.2284)	(0.1212)	(0.2117)	(0.2144)	(0.1281)	(0.1766)	(0.1863)	(0.1589)
	[0.5238]	[0.3870]		[0.3218]	[0.4661]		[0.0827]	[0.9090]	
Corr($\Delta_4 p_t, \Delta_4 a_{t+1}$)	0.3430	0.4329	0.2753	-0.1095	-0.1549	-0.3264	-0.1294	0.1762	-0.0221
	(0.2237)	(0.2231)	(0.1179)	(0.2164)	(0.2163)	(0.1421)	(0.1581)	(0.1733)	(0.1695)
	[0.7890]	[0.5323]		[0.4020]	[0.5074]		[0.6435]	[0.4133]	
moments closer to data	6	2		2	6		2	6	
moments rejected at 5%	1	0		0	1		0	0	
$\log_{10} \Pi_{x \in X} f(x)$	-7.66	-13.24		-219.82	-323.00		2.08	-1.76	

Table 3 continued.

For Germany, no moment is rejected under the estimated parametrization. Sticky prices match more moments closer and the model has the higher likelihood.

Considering France, sticky information wins the horse race under the estimated parametrization. The sticky-information model performs considerably better than under the baseline calibration whereas the performance of sticky prices does not change much. Sticky information has the higher density and matches more moments more closely.

Concerning Canada, sticky information is not better than sticky prices. Using the estimated parameters, both models improve as less moments are rejected, but at at the cost of lower overall likelihoods. Comparing the model performances, no clear evidence occurs.

Also, the results for Japan allow no clear discrimination between models. For both models, no moment is rejected but sticky price match six moments closer. By contrast, sticky information has the higher likelihood.

Also, under the estimated parametrization we want to draw special attention to the unusual moments which the models failed to generate under the baseline calibration (see Section 3.1). Also here, both models substantially overpredict the relatively low Canadian inflation persistence. This indicates that the two models systematically generate too much inflation smoothness. This result is in line with those of previous studies. In Coibion (2010), the poor performance of the sticky-information approach is partly driven by the fact that predicted inflation is excessively smooth. Also in the study of Paustian and Pytlarczyk (2006), the origin of the poor fit of sticky information is the inability of the model to match the autocorrelation of inflation. With respect to the negative correlations of inflation with movements in demand (UK and Canada), the sticky-price model is rather successful under the estimated parametrization. The model now predicts four of the six negative signs correctly while still generating all the positive signs in the other countries. In this respect, the sticky information model performs even worse than under the baseline calibration, a consequence of the improved fit in the unconditional moments of inflation dynamics (see above).

All in all, the comparison of the estimated models shows weak support for one of the competing models in three countries. Sticky prices perform slightly better in the UK and Germany, while sticky information is supported by French data. Performances of the two models are very similar in the other three countries.

4 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 contributed to the literature on the horse race between the two concepts methodologically in several respects. We compared the model performances both in moment-based and likelihood evaluations. In addition, we took a broad look on inflation dynamics considering inflation variance and persistence as well as its relation to dynamics in demand and supply. Finally, our cross-country perspective allowed to test whether model performances are country-specific.

We performed two comparisons of sticky prices and sticky information. In the first we compared calibrated versions of the two models, whereas we considered estimated models in the second comparison. Our results do not clearly support one of the two competing models. Relative model performances depend on the calibration, the country, and on which moments of the inflation process one focuses.

In the baseline calibration, the two models perform similarly in most countries. Only in the UK, sticky information is clearly supported. When comparing the estimated models, our results indicate that sticky information performs better in France, while sticky prices dominate in the UK and Germany and both models perform similarly in the US, Canada, and Japan.

The cross-country perspective of our paper revealed that both models' performances worsen where inflation dynamics deviate from US observations. Our broad view on the inflation process allowed disentangling the model performances. We find that sticky prices match unconditional moments of inflation dynamics better while sticky information is more successful in matching co-movement of inflation with demand.

References

Abbott, B. (2010). Sticky information vs. sticky prices vs. sticky prices with indexation: A formal test of the dynamic response to a monetary shock. Technical report, University of British Columbia.

Andrés, J., J. D. López-Salido, and E. Nelson (2005). Sticky-price models and the natural rate hypothesis. *Journal of Monetary Economics 52*(5), 1025–1053.

Carroll, C. D. (2003). Macroeconomic expectations of households and professional forecasters. *The Quarterly Journal of Economics 118*(1), 269–298.

Chari, V. V., P. J. Kehoe, and E. R. McGrattan (2000). Sticky price models of the business cycle: Can the contract multiplier solve the persistence problem? *Econometrica 68*(5), 1151–1180.

Ciobîcă, I. (2010). Inflation dynamics under the sticky information Phillips curve. DOFIN Working Paper 41, Bucharest University of Economics.

Coibion, O. (2010). Testing the sticky information Phillips curve. *The Review of Economics and Statistics 92*(1), 87–101.

Davidson, R. and J. G. MacKinnon (2004). *Econometric Theory and Methods*. Oxford University Press.

Döpke, J., J. Dovern, U. Fritsche, and J. Slacalek (2008). Sticky information Phillips curves: European evidence. *Journal of Money, Credit and Banking 40*(7), 1513–1520.

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

Elfron, B. and R. J. Tibshirani (1998). *An introduction to the bootstrap*. Chapman & Hall/CRC.

Khan, H. and Z. Zhu (2002). Estimates of the sticky-information Phillips curve for the United States, Canada, and the United Kingdom. Bank of Canada Working Paper 02-19.

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.

Korenok, O. (2008). Empirical comparison of sticky price and sticky information models. *Journal of Macroeconomics 30*(3), 906–927.

Korenok, O. and N. R. Swanson (2007). How sticky is sticky enough? A distributional and impulse response analysis of new Keynesian DSGE models. *Journal of Money, Credit and Banking 39*(6), 1481–1508.

Laforte, J.-P. (2007). Pricing models: A Bayesian DSGE approach for the U.S. economy. *Journal of Money, Credit and Banking 39*(s1), 127–154.

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

Mankiw, N. G. and R. Reis (2011). Imperfect information and aggregate supply. In B. Friedman and M. Woodford (Eds.), *Handbook of Monetary Economics*, pp. 183–230. Elsevier-North Holland.

Paustian, M. and E. Pytlarczyk (2006). Sticky contracts or sticky information? Evidence from an estimated euro area DSGE model. *mimeo.*

Reis, R. (2006). Inattentive producers. *Review of Economic Studies 73*(3), 793–821.

Smets, F. and R. Wouters (2003). An estimated dynamic stochastic general equilibrium model of the Euro area. *Journal of the European Economic Association 1*(5), 1123–1175.

A Appendix

A.1 Model Solution

We determine the model solution by a guess-and-verify approach. We guess that inflation is a moving average of past shocks, see equation (5).

A.1.1 Sticky Information

We start from the Sticky-information Phillips curve (2). In this appendix, we solve for the coefficients on Δm_t, the solution for the coefficients on Δa_t is equivalent except for the opposite sign. We solve for coefficients on Δm_t using the method of undetermined coefficients. First, we consider $\Delta a_{t+i} = 0$ $\forall i$. Our guessed solution for inflation (5) then simplifies to

$$\pi_t = \sum_{i=0}^{\infty} \gamma_i^{SI} \varepsilon_{t-i}^m. \tag{6}$$

Plugging the solution for inflation into (2) yields:

$$\sum_{i=0}^{\infty} \gamma_i^{SI} \varepsilon_{t-i}^m = \left[\frac{\alpha\lambda}{1-\lambda}\right] y_t + \lambda \sum_{j=0}^{\infty} (1-\lambda)^j E_{t-1-j} \left(\sum_{i=0}^{\infty} \gamma_i^{SI} \varepsilon_{t-i}^m + \alpha \Delta y_t \right)$$

Thus expressions for the log output gap and the log output gap growth are needed. Using the definition of the output gap, the MA representation of nominal income growth (4),

$$\Delta m_t = \sum_{i=0}^{\infty} \chi_i \varepsilon_{t-i}^m,$$

and the assumption of $\Delta a_{t+i} = a_{t+i} = 0$ $\forall i$ gives an expression for the log output gap growth:

$$\begin{aligned} \Delta y_t &= \Delta m_t - \Delta p_t \\ &= \sum_{i=0}^{\infty} \chi_i \varepsilon_{t-i}^m - \sum_{i=0}^{\infty} \gamma_i^{SI} \varepsilon_{t-i}^m \end{aligned} \tag{7}$$

The log output y_t can be described by using equation (7) as:

$$\begin{aligned}
y_t &= \sum_{i=0}^{\infty} \chi_i \varepsilon_{t-i}^m - \sum_{i=0}^{\infty} \gamma_i^{SI} \varepsilon_{t-i}^m + y_{t-1} \\
&= \sum_{i=0}^{\infty} \chi_i \left[\sum_{k=0}^{\infty} \varepsilon_{t-k-i}^m \right] - \sum_{i=0}^{\infty} \gamma_i^{SI} \left[\sum_{k=0}^{\infty} \varepsilon_{t-k-i}^m \right] \qquad (8)
\end{aligned}$$

Substituting (7) and (8) into the Phillips curve (2):

$$\begin{aligned}
\sum_{i=0}^{\infty} \gamma_i^{SI} \varepsilon_{t-i}^m &= \left[\frac{\alpha\lambda}{1-\lambda} \right] \left\{ \sum_{i=0}^{\infty} \chi_i \left[\sum_{k=0}^{\infty} \varepsilon_{t-k-i}^m \right] - \sum_{i=0}^{\infty} \gamma_i^{SI} \left[\sum_{k=0}^{\infty} \varepsilon_{t-k-i}^m \right] \right\} \\
&\quad + \lambda \sum_{j=0}^{\infty} (1-\lambda)^j E_{t-1-j} \left\{ \sum_{i=0}^{\infty} \gamma_i^{SI} \varepsilon_{t-i}^m \right. \\
&\quad \left. + \alpha \left[\sum_{i=0}^{\infty} \chi_i \varepsilon_{t-i}^m - \sum_{i=0}^{\infty} \gamma_i^{SI} \varepsilon_{t-i}^m \right] \right\} \qquad (9) \\
&= \left[\frac{\alpha\lambda}{1-\lambda} \right] \left\{ \sum_{i=0}^{\infty} \chi_i \left[\sum_{k=0}^{\infty} \varepsilon_{t-k-i}^m \right] - \sum_{i=0}^{\infty} \gamma_i^{SI} \left[\sum_{k=0}^{\infty} \varepsilon_{t-k-i}^m \right] \right\} \\
&\quad + \lambda \sum_{j=0}^{\infty} (1-\lambda)^j \left\{ (1-\alpha) \sum_{i=j+1}^{\infty} \gamma_i^{SI} \varepsilon_{t-i}^m + \alpha \sum_{i=j+1}^{\infty} \chi_i \varepsilon_{t-i}^m \right\}
\end{aligned}$$

Because (9) must hold for all possible realizations of ε_{t-j-k}^m, we can use $\varepsilon_t^m = 1$, $\varepsilon_{t-u}^m = 0 \ \forall u > 0$ to determine the coefficient γ_0^{SI}. Under this realization, equation (9) simplifies to:

$$\begin{aligned}
\gamma_0^{SI} &= \left[\frac{\alpha\lambda}{1-\lambda} \right] \left\{ \chi_0 - \gamma_0^{SI} \right\} \\
&= \left[\frac{\alpha\lambda}{1-\lambda} \right] \left\{ 1 - \gamma_0^{SI} \right\} \\
&\Leftrightarrow \ \gamma_0^{SI} = \left[\frac{\alpha\lambda}{1-\lambda+\alpha\lambda} \right]
\end{aligned}$$

For a general k, we use the realization $\varepsilon_{t-k}^{m}=1$, $\varepsilon_{t-u}^{m}=0\ \forall u\neq k$ for which (9) becomes:

$$\begin{aligned}
\gamma_k^{SI} &= \left[\frac{\alpha\lambda}{1-\lambda}\right]\left\{\sum_{i=0}^{k}\chi_i-\sum_{i=0}^{k}\gamma_i^{SI}\right\}+\lambda\sum_{i=0}^{k-1}(1-\lambda)^j\left\{(1-\alpha)\,\gamma_k^{SI}+\alpha\chi_k\right\} \\
&= \left[\frac{\alpha\lambda}{1-\lambda}\right]\left\{\sum_{i=0}^{k}\chi_i-\sum_{i=0}^{k}\gamma_i^{SI}\right\}+\lambda\left\{(1-\alpha)\,\gamma_k^{SI}+\alpha\chi_k\right\}\cdot\sum_{i=0}^{k-1}(1-\lambda)^i \\
\gamma_k^{SI} &= \alpha\lambda\left(1-\lambda\,(1-\alpha)\sum_{i=0}^{k}(1-\lambda)^i\right)^{-1} \\
&\quad\cdot\left[1-\sum_{i=0}^{k-1}\gamma_i^{SI}+\sum_{i=1}^{k}\chi_i+\chi_k\sum_{i=1}^{k}(1-\lambda)^i\right]
\end{aligned}$$

A.1.2 Sticky Prices

We start from the following representation of the Sticky-price Phillips curve (1),

$$p_t=\theta p_{t-1}+(1-\theta)^2\sum_{i=0}^{\infty}\theta^i E_t\left(m_{t+i}-a_{t+i}\right), \tag{10}$$

which is equation (A13) from Mankiw and Reis (2002) extended with a non-constant log productivity a_t. In this appendix, we solve for the coefficients on innovations to nominal income, the solution for the coefficients on innovations to productivity is again equivalent except for the opposite sign.

We solve for coefficients on Δm_t using the method of undetermined coefficients. For convenience, we assume $\Delta a_{t+i}=0\ \forall i$. Our guessed solution for inflation (5) then simplifies to

$$\pi_t=\sum_{i=0}^{\infty}\gamma_i^{SP}\varepsilon_{t-i}^{m}. \tag{11}$$

We also use the MA representation of nominal income growth (4). Eliminating the difference operator by backward iteration yields

$$p_t = \sum_{j=0}^{\infty}\gamma_j^{SP}\sum_{k=0}^{\infty}\varepsilon_{t-j-k}^{m} \tag{12}$$

$$m_t = \sum_{j=0}^{\infty} \chi_j \sum_{k=0}^{\infty} \varepsilon_{t-j-k}^m \tag{13}$$

Plugging (12) and (13) into (10) gives

$$\sum_{j=0}^{\infty} \gamma_j^{SP} \sum_{k=0}^{\infty} \varepsilon_{t-j-k}^m = \theta \sum_{j=0}^{\infty} \gamma_j^{SP} \sum_{k=0}^{\infty} \varepsilon_{t-j-k-1}^m + (1-\theta)^2 \sum_{i=0}^{\infty} \theta^i E_t \sum_{j=0}^{\infty} \chi_j \sum_{k=0}^{\infty} \varepsilon_{t-j-k+i}^m$$

which can be simplified to

$$\begin{aligned}\sum_{j=0}^{\infty} \gamma_j^{SP} \sum_{k=0}^{\infty} \varepsilon_{t-j-k}^m =& \theta \sum_{j=0}^{\infty} \gamma_j^{SP} \sum_{k=0}^{\infty} \varepsilon_{t-j-k-1}^m \\ &+ (1-\theta)^2 \sum_{i=0}^{\infty} \theta^i \sum_{j=0}^{\infty} \chi_j \sum_{k=\max(i-j,0)}^{\infty} \varepsilon_{t-j-k+i}^m.\end{aligned} \tag{14}$$

Using matching coefficients as described in the preceding section (use the realization $\varepsilon_t^m = 1$, $\varepsilon_{t-u}^m = 0\ \forall u > 0$ in (14)) yields for γ_0^{SP}:

$$\begin{aligned}\gamma_0^{SP} &= 0 + (1-\theta)^2 \sum_{i=0}^{\infty} \theta^i \sum_{j=0}^{i} \chi_j = (1-\theta)^2 \sum_{i=0}^{\infty} \chi_i \sum_{j=i}^{\infty} \theta^j \\ &= (1-\theta)^2 \sum_{i=0}^{\infty} \chi_i \left\{ \sum_{j=0}^{\infty} \theta^j - \sum_{j=0}^{i-1} \theta^j \right\} = (1-\theta)^2 \sum_{i=0}^{\infty} \chi_i \left\{ \frac{1}{1-\theta} - \frac{\theta^i - 1}{\theta - 1} \right\} \\ &= (1-\theta)^2 \sum_{i=0}^{\infty} \chi_i \cdot \frac{-\theta^i}{\theta - 1} = (1-\theta) \sum_{i=0}^{\infty} \theta^i \chi_i.\end{aligned}$$

and for γ_j^{SP} (using $\varepsilon_{t-j}^m = 1$, $\varepsilon_{t-u}^m = 0\ \forall u \neq j$ in (14))

$$\begin{aligned}\sum_{j=0}^{v} \gamma_j^{SP} &= \theta \sum_{j=0}^{v-1} \gamma_j^{SP} + (1-\theta)^2 \sum_{i=0}^{\infty} \theta^i \sum_{j=0}^{v+i} \chi_j \\ &\Leftrightarrow \gamma_v^{SP} + \sum_{j=0}^{v-1} \gamma_j^{SP} = \theta \sum_{j=0}^{v-1} \gamma_j^{SP} + (1-\theta)^2 \sum_{i=0}^{\infty} \theta^i \sum_{j=0}^{v+i} \chi_j \\ &\Leftrightarrow \gamma_v^{SP} = (\theta - 1) \sum_{j=0}^{v-1} \gamma_j^{SP} + (1-\theta)^2 \sum_{i=0}^{\infty} \theta^i \sum_{j=0}^{v+i} \chi_j \end{aligned} \tag{15}$$

The double sum $\sum_{i=0}^{\infty}\theta^i\sum_{j=0}^{v+i}\chi_j$ at the right hand side of (15) can be expressed as follows:

$$\begin{aligned}
\sum_{i=0}^{\infty}\theta^i\sum_{j=0}^{v+i}\chi_j &= \sum_{i=0}^{\infty}\chi_i\sum_{j=\max(0,i-v)}^{\infty}\theta^j \\
&= \sum_{i=0}^{\infty}\chi_i\left\{\sum_{j=0}^{\infty}\theta^j-\sum_{j=0}^{i-v-1}\theta^j\right\} \\
&= \sum_{i=0}^{\infty}\chi_i\left\{\frac{1}{1-\theta}-\max\left(\frac{\theta^{i-v}-1}{\theta-1},0\right)\right\} \\
&= \frac{1}{1-\theta}\sum_{i=0}^{\infty}\chi_i-\sum_{i=v}^{\infty}\chi_i\left(\frac{\theta^{i-v}-1}{\theta-1}\right) \\
&= \frac{1}{1-\theta}\left[\sum_{i=0}^{\infty}\chi_i-\sum_{i=v}^{\infty}\chi_i\left(1-\theta^{i-v}\right)\right] \\
&= \frac{1}{1-\theta}\left[\sum_{i=0}^{\infty}\chi_i-\sum_{i=v}^{\infty}\chi_i+\sum_{i=v}^{\infty}\chi_i\theta^{i-v}\right] \\
&= \frac{1}{1-\theta}\left[\sum_{i=0}^{v-1}\chi_i+\sum_{i=v}^{\infty}\chi_i\theta^{i-v}\right]
\end{aligned}$$

Using this, (15) becomes

$$\begin{aligned}
\gamma_v^{SP} &= (\theta-1)\sum_{j=0}^{v-1}\gamma_j^{SP}-(\theta-1)\left[\sum_{i=0}^{v-1}\chi_i+\sum_{i=v}^{\infty}\chi_i\theta^{i-v}\right] \\
&\Leftrightarrow\ \gamma_v^{SP}=(\theta-1)\left\{\sum_{j=0}^{v-1}\gamma_j^{SP}-\sum_{i=0}^{v-1}\chi_i-\sum_{i=v}^{\infty}\chi_i\theta^{i-v}\right\}.
\end{aligned}$$

A.2 Empirical Strategy: Formal Description

Model Comparison. In detail, our empirical procedure under a certain parametrization, α and λ, proceeds as follows: For each country c and model z, the analysis consists of a complete model parametrization and a repeated model simulation and proceeds as follows:

1. In the parametrization phase, 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).[5] Having found such an auto-regressive process, we invert it into its MA representation. We collect the values for the coefficients $\{\chi_i^c\}$ and $\{\omega_i^c\}$ and the innovation variances $\sigma_{m,c}^2$ and $\sigma_{a,c}^2$ governing the dynamics of nominal income growth and productivity growth for this country in $\Omega_c = \left\{ \{\chi_i^c\}_{i=0}^{\infty}, \sigma_{m,c}^2, \{\omega_i^c\}_{i=0}^{\infty}, \sigma_{a,c}^2 \right\}$. The model is now completely quantified, the parametrization is described by $\alpha_{c,z}$, $\lambda_{c,z}$, and Ω_c.[6]

2. Using the values for the coefficients $\{\chi_i^c\}$ and $\{\omega_i^c\}$ and the parameters α and λ_c, we calculate the coefficients $\{\gamma_i^{c,z}\}$ and $\{\xi_i^{c,z}\}$ in the MA representation of inflation (5).

3. Combining the sequence of residuals, derived from estimating (3) and (4) in step 1, with the MA coefficients from (5) derived in step 2, we calculate a sequence of quarterly inflation rates Δp_t predicted by model z for country c. We then calculate selected second moments of corresponding annual changes. Specifically, we calculate the following set of second moments X:

$$X = \left\{ \begin{array}{c} S.D.(\Delta_4 p_t), Corr(\Delta_4 p_t, \Delta_4 p_{t-1}), \\ Corr(\Delta_4 p_t, \Delta_4 m_t), Corr(\Delta_4 p_t, \Delta_4 m_{t-1}), Corr(\Delta_4 p_t, \Delta_4 m_{t+1}), \\ Corr(\Delta_4 p_t, \Delta_4 a_t), Corr(\Delta_4 p_t, \Delta_4 a_{t-1}), Corr(\Delta_4 p_t, \Delta_4 a_{t+1}) \end{array} \right\}$$

These moments can be compared to the empirical moments on the basis of absolute deviations. This, however, ignores the statistical properties of the moments and thus does not allow inference.

[5] Concerning Canada and Japan, we use eight lags in the processes for Δa_t and Δm_t as we found that estimation precision on subsequent stages improves substantially.

[6] In the comparison of the calibrated models, $\alpha_{c,z} = 0.11$, $\lambda_{c,z} = 0.25\ \forall c, z$. In the comparison of the estimated models, $\alpha_{c,z}$ and $\lambda_{c,z}$ refer to the estimated parameters.

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 normal distributions with mean zero and variances $\sigma_{m,c}^2$ or $\sigma_{a,c}^2$ 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 inflation rates $\{\pi_t^{c,z}\}$ as predicted by the respective model z given Ω_c.

   For each simulation, we calculate the standard deviation of inflation, its auto-correlation, and its cross-correlations to current values, leads, and lags of nominal income and productivity growth. We thus generate a distribution of model moments by simulation. The resulting distributions are well approximated by normal distributions. For each moment $x \in X$, we then estimate a density function $f_x^{c,z}(x|\alpha, \lambda_c, \Omega_c)$ from the 10,000 generated observations using Maximum Likelihood. We use the function $f_x^{c,z}(x|\alpha, \lambda_c, \Omega_c)$ 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 (Elfron and Tibshirani 1998, Chapter 8.6).

Estimation. For each country c and model z, we estimate the degrees of rigidity, α and λ, using the method of simulated moments described by Davidson and MacKinnon (2004, Chapter 9.6). Our vector of moments X is the same as used in the model evaluation. The function to be minimized is a weighted average of the squared differences between empirical and model moments,

$$Q(\alpha, \lambda, X^{c,z}, X^c) = \frac{1}{n} \cdot [X^{c,z}(\alpha, \lambda, \Omega_c) - X^c]' \cdot W \cdot [X^{c,z}(\alpha, \lambda, \Omega_c) - X^c],$$

where n is the number of observations for each moment. The vector of mean model moments $X^{c,z}(\alpha, \lambda, \Omega_c)$ is determined as described in steps 2 and 3 above. X^c is the vector of empirical moments. The weighting matrix W is the covariance matrix of $X^{c,z}(\alpha, \lambda, \Omega_c) - X^c$ and is determined by bootstrapping from the innovations to nominal income and productivity using the method

	"true" value	Mean estimator	5% quantile	95% quantile
SI: α	0.1100	0.1669	0.0567	0.3317
SI: λ	0.2500	0.1756	0.0861	0.2934
SP: α	0.1100	0.0643	0.0210	0.1179
SP: λ	0.2500	0.2403	0.2157	0.2658

Table 4: Monte Carlo study, estimated α and λ for both models

of moving blocks bootstrap (Elfron and Tibshirani 1998, Chapter 8.6). The estimators $\alpha_{c,z}$ and $\lambda_{c,z}$ are the solution to $\min_{\alpha,\lambda} Q\left(\alpha, \lambda, X^{c,z}, X^{c}\right)$. We compare the models under the estimated parametrization repeating the described above using $\alpha_{c,z}$ and $\lambda_{c,z}$.

Monte Carlo Study. We check the reliability of the estimation procedure in a Monte Carlo study using 10,000 simulated data sets of length 80 (the length of our US data set). These data sets stem from simulations of the respective models under a pre-determined parametrization. The results (Table 4) of the Monte Carlo study confirm our confidence in the estimation procedure, no estimator is significantly biased.

A.3 Data

For our empirical analysis, data on inflation, productivity, and nominal income is needed. We have quarterly data on these three variables for a sufficiently long period for the following six countries: the US, the UK, Germany, France, Canada, and Japan. However, the period for which we have complete data varies considerably between the different countries.

For inflation and nominal income, we use CPI inflation and nominal GDP per capita, respectively, for all countries. Concerning labor productivity which we use as a measure of natural output, our variable of choice is output per working person which we have for five countries. For reasons of data availability, we use productivity per working hour for Germany.

The longest sample is available for the US. For comparability with Reis (2006), we use the same US sample. For Canada, the shortest sample in our data set, only data from the first quarter of 1981 is available for all three variables. All data is taken from the OECD, Datastream, and national statistical offices.[7] Table 5 provides sources and details on the data used.

Country	Nominal GDP	CPI	Productivity	Sample period
US	Bureau of Economic Analysis; Table 1.1.5. Gross Domestic Product [Billions of dollars]; Seasonally adjusted at annual rates	Bureau of Labor Statistics; Series Id: CUUR0000SA0; Not Seasonally Adjusted Area: U.S. city average Item: All items; Base Period: 1982-84=100	Bureau of Labor Statistics; Output per Person; Nonfarming Sector; 1992=100	1960 to 2003
UK	Office for National Statistics UK; ABMI; Gross Domestic Product; Chained volume measures; Seasonally adjusted; Constant 2003 prices	OECD; Index 2005=100	Office for National Statistics UK; A4YM; Output per Worker; Whole Economy SA; Index 2003=100; Seasonally adjusted	1959 to 2008
Germany	Bundesamt für Statistik; before 1990 West Germany; linear extrapolation of growth rate in 1990Q1	OECD; Index 2005=100	Bundesbank; Productivity per hour; Seasonally adjusted; Index 1995=100	1970 to 2008
France	INSEE National Institute of Statistics and Economic Studies	OECD; Index 2005=100	National Institute of Statistics and Economic Studies; GDP per employed person	1978 to 2008
Canada	Datastream	OECD; Index 2005=100	Cansim; Labour productivity; Total economy	1981 to 2008
Japan	DSI Data Service; Seasonally adjusted	OECD; Index 2005=100	Datastream; Labour productivity; Total economy	1970 to 2008

Table 5: Sample periods, data sources, and details.

A.4 Nominal Income and Productivity Processes

Table 6 reports the estimated auto-regressive processes for nominal income and productivity growth for the six countries in our sample. The order of the processes has been determined by sequential t-testing. In 5 of the 12 cases, it is sufficient to use not more than one lag to describe the dynamics in productivity and nominal income growth in the various countries. Growth in nominal income can be described as an AR(1) process for the United States. For the UK, nominal income growth seems to be i.i.d. For Germany, France, Canada and Japan, growth of nominal income is best described by auto-regressive processes of higher order. Productivity growth can be described

[7] In the first quarter of 1990, a linear extrapolation for nominal income growth is used for Germany in consideration of the re-unification.

nominal income growth						
	cons $\cdot\ 10^2$	$t-1$	$t-2$	$t-3$	$t-4$	$\sigma_m^2 \cdot 10^4$
US	1.0700 (0.1290)	0.3788 (0.0655)				0.8147
UK	0.6060 (0.0695)					0.9511
Germany	0.3154 (0.1573)	0.0371 (0.0775)	0.1489 (0.0760)	0.1373 (0.0759)	0.3667 (0.0747)	0.8875
France	0.1309 (0.0904)	0.4798 (0.0863)	0.3985 (0.0851)			0.2772
Canada	0.3257 (0.1112)	0.5301 (0.0966)	-0.0450 (0.1059)	0.3057 (0.1058)	-0.2561 (0.1097)	0.2933
Japan	0.0516 (0.1197)	0.1445 (0.0808)	0.2882 (0.0823)	0.2282 (0.0858)	0.1731 (0.0886)	1.0226
productivity growth						
	cons $\cdot 10^2$	$t-1$	$t-2$	$t-3$	$t-4$	$\sigma_a^2 \cdot 10^4$
US	0.5437 (0.0602)					0.7218
UK	0.4994 (0.0635)					0.7933
Germany	0.9054 (0.1017)					1.6026
France	0.2822 (0.0626)	-0.0258 (0.0913)	0.2329 (0.0885)			0.1834
Canada	0.2198 (0.0848)	0.1285 (0.0971)	-0.0762 (0.0967)	0.2828 (0.0953)	-0.0487 (0.0987)	0.2043
Japan	0.2129 (0.1580)	0.4923 (0.0955)	0.2305 (0.1061)	-0.0006 (0.1059)	-0.2848 (0.1042)	3.0287

Table 6: Estimated coefficients and shock variances for productivity and nominal income growth processes.

Notes: For Canada and Japan, the coefficients on the lags 5 to 8 are: Canada, nominal income: 0.0196 (0.1091), 0.0144 (0.1056), 0.0626 (0.1040), -0.1057 (0.0906). Canada, productivity: 0.0191 (0.0993), 0.0851 (0.0963), -0.0284 (0.0931), -0.1208 (0.0909). Japan, nominal income: 0.0939 (0.0889), 0.0976 (0.0872), -0.0201 (0.0834), -0.1056 (0.0832). Japan, productivity: -0.2175 (0.1043), 0.2186 (0.1057), 0.1175 (0.1052), -0.3015 (0.0955).

as i.i.d. with positive mean for the US, the UK, and Germany. French, Canadian, and Japanese growth rates show some significant auto-regressive components.