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Sources and Channels of Nonlinearities and Instabilities of the Phillips Curve: Results for the Euro Area and Its Member States

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Abstract

This paper presents evidence for sources and channels of nonlinearities and instabilities of the new Keynesian Phillips curve (NKPC) for the euro area and all but four member states over the last two decades prior to the COVID-19 crisis. The approach rests upon misspecification testing using auxiliary regressions based on the standard open-economy hybrid NKPC. Using a large number of specifications, this approach allows to systematically, i. e., based on a literature review, disentangle the evidence for nonlinearities and instabilities of the NKPC according to sources and channels. For the euro area and most considered member states, there is substantial evidence for nonlinearities and instabilities. The relatively most important channels of nonlinearities and instabilities are similar across countries, whereas the relatively most important sources differ across countries. The results strongly indicate the need for considering nonlinear NKPC relationships in empirical analyses and also point towards potentially useful nonlinear specifications.

JEL Classification: E31, E52, E58, F62, J11

Keywords: Euro area, instability, new Keynesian Phillips curve, nonlinearity, specification analysis

1 Introduction

With the recent surge in inflation during the COVID-19 crisis, the Phillips curve remains in the center of attention of policy-makers in general and in particular of central banks. Before the COVID-19 crisis, the Phillips curve was typically investigated in relation to a "missing inflation" puzzle after the great financial crisis (GFC), see, e. g., the work of the ECBs Task Force on Low Inflation (LIFT) summarized in Ciccarelli and Osbat (2017).

The exact reasons why inflation has remained low after the GFC, although the economy has been growing faster than potential, are still unclear and highly debated. Ciccarelli and Osbat (2017) find that cyclical domestic drivers (like slack or economic activity and lagged inflation) and global drivers (like external cost-push shocks, typically modeled by imported inflation measures) have played an important role. In addition, Lagarde (2020) points towards potentially important contributions of long-term structural factors ("secular trends") like demographic trends, globalization and digitalization and problems with accurate measurement of (unobserved) slack to the low inflation period.[1] While monetary policy is usually able to offset the effects of these secular trends, being in the vicinity of the effective lower bound limits the monetary policy space and might foster negative effects of secular trends on inflation (compare Koester *et al.*, 2021). Moreover, short-term interest rates close to the effective lower bound might also have implications for (short- and long-run) inflation expectations formation and thus on current inflation (compare, e. g., Kamber *et al.*, 2020).

Based on the underlying observation of a potential flattening of the Phillips curve, a large and still growing literature investigates different *sources* and/or different transmission *channels* that impact the linearity and/or stability of the Phillips curve in general or the current New Keynesian Phillips Curve (NKPC) workhorse variants in particular.[2] Whilst most contributions investigating the linearity and/or stability of the Phillips curve zoom in on specific sources or channels, this paper sets out to systematically investigate the sources of nonlinearities and instabilities as well as corresponding transmission channels in standard formulations of open-economy new Keynesian Phillips curves as used

[1] Slack is broadly interpreted and refers to real disequilibria rather than to a specific measure of the output gap only in the literature (see, e. g., Szörfi and Tóth, 2018).

[2] In this paper, nonlinearity and instability in the context of NKPCs refer to evidence that usual time-invariant linear formulations used in empirical analysis do not provide good fit, i. e., can be rejected by, e. g., econometric specification analysis. NKPCs are, of course, highly nonlinear relationships in basically all underlying economic models. In relation to this obvious point, the discussion in Cogley and Sbordone (2008) highlights that, e. g., structural instability driven by (in their example) time-varying trend inflation impacts the significance of variables (in their case past inflation rates) in estimated baseline time-invariant linear NKPCs.

in, e. g., LIFT (Ciccarelli and Osbat, 2017).[3] Our empirical analysis uses quarterly data with country-specific samples beginning between 2003Q1 and 2007Q1 and ranging until at latest 2020Q1 for the euro area as well as 15 member states, i. e., all member states excluding Estonia, Ireland, Malta and Portugal.[4] We address the uncertainty of slack measurement by using altogether seven different measures of slack or economic activity and investigate the implications of using these different measures for our findings.[5] In a similar spirit, we consider six different measures of imported inflation.[6] Importantly, by considering the euro area aggregate and the individual member states separately, our approach also allows to assess the extent of cross-country heterogeneity of sources and channels of nonlinearities and instabilities across euro area members.

As detailed in Section 2, the investigation of sources and channels of nonlinearities and instabilities is based on (mis-)specification testing, using a large number of potential sources of nonlinearities and instabilities and a variety of channels through which these sources may affect inflation dynamics. To be precise, we test the null hypothesis of correct specification against the alternative of misspecification by estimating auxiliary test regressions. This approach is most closely related to testing the null hypothesis of linearity against the alternative of smooth transition regressions (STRs). Section 2.2 discusses our approach in detail and elaborates why our testing approach is a useful "shotgun" also against other forms of nonlinearities and instabilities than the STR alternative. Sticking to the STR framework for notational simplicity, the source of nonlinearities and instabilities refers to the transition variable and the channel refers to the set of variables interacted nonlinearly with the transition variable through the transition function. Rejections of the null hypothesis of linearity for certain (combinations of) sources and channels, or more precisely, a larger number of rejections of the null for certain (combinations of) sources and channels, thus serves as evidence for the "relative importance" of these sources and channels for modeling nonlinearities and instabilities of the NKPC. Given our data set,

[3] Section 2.2 pins down the precise meanings of the terms "source" and "channel" used in this paper in the context of nonlinearities and instabilities in NKPCs.

[4] Our data set is an updated and extended version of the data set used by LIFT. For Estonia, Ireland and Portugal the data could not be updated beyond 2014Q4, whereas Malta is excluded from the analysis because of many missing variables. Not all variables are available for all included countries, with the details given in Tables A.1 and A.2 in Appendix A.

[5] These seven measures are real GDP growth, the unemployment rate, the output gap, the unemployment gap, capacity utilization, real investment growth and total employment growth. See Table A.1 in Appendix A for details and sources. Please note that in the following, the term "slack (measure)" refers to all seven variables and is denoted by y.

[6] These six measures are oil prices, import prices, non-energy commodity prices (all in annual growth rates), the EUR/USD exchange rate, foreign demand (import demand of extra euro area trading partners, annual growth rate) and a variable related to euro area farm gate prices (annual growth rate). See Table A.1 in Appendix A for details and sources. Section 3.3 discusses the impact of using different slack and imported inflation measures on the results.

the relative importance of sources and channels can also be compared across the euro area and the considered 15 member states as well as across different measures of slack and imported inflation.

For the euro area and all considered member states, there is evidence for nonlinearities and instabilities of the Phillips curve, with the average rejection rate across countries and the euro area equal to a third. The largest rejection rate occurs for the euro area and the smallest for Cyprus. The most important channels for modeling these nonlinearities and instabilities appear to be the intercept and the long-run inflation mean, whereas nonlinearities and instabilities in the effect of slack on inflation seem to be of secondary importance only. The major sources of nonlinearities are highly country-specific, and often several sources feature prominently. When considered as sources, both cyclical drivers like slack as well as the short-term interest rate, here measured as the 3-month EONIA rate, appear to be important determinants of nonlinearities and instabilities of the Phillips curve. An additional key finding is that strong evidence for nonlinearities and instabilities is also found in relation to long-term structural factors like demographic trends. Moreover, it turns out that both the choice of slack measures and the choice of imported inflation measures matter for the results. In this context, it is particularly noteworthy that for the euro area and several member states some combinations of channels and sources lead to rejections of the null hypothesis of correct specification for all slack and imported inflation measures.

The paper is organized as follows: Section 2 consists of three subsections. The first subsection collects evidence for potential nonlinearities and instabilities in the baseline NKPC specification, the second discusses the misspecification testing approach and the third provides a short literature review that forms the basis for the selection of channels and sources. Section 3 presents the results and Section 4 summarizes and concludes. The Appendix provides details on the data and contains additional empirical results.

2 The Framework for the Empirical Analysis

2.1 The Baseline Specification

The starting point of our analysis is a standard open-economy hybrid new Keynesian Phillips curve:[7]

$$
\begin{aligned}
\pi_t &= \beta_0 + \sum_{j=1}^{p^*} \beta_j \pi_{t-j} + \beta_e \pi_t^e + \beta_y y_{t-1} + \beta_m \pi_{t-2}^m + \varepsilon_t \\
&= Z_t' \beta + \varepsilon_t, \qquad (2.1)
\end{aligned}
$$

with π_t the annual growth rate of the harmonized index of consumer prices, π_t^e short-run inflation expectations, y_t one of the up to seven considered measures of slack (or economic activity) and π_t^m one of the up to six considered measures of imported inflation, see Table A.1 in Appendix A for details on the variables. The error term ε_t is assumed to be serially uncorrelated, typically achieved in practice by an appropriate choice of p^*. The formulation given in (2.1), in particular the choice of the first lag of the slack measure and of the second lag of the imported inflation measure as regressors, is similar to the specification considered in LIFT (see Ciccarelli and Osbat, 2017, p. 22).

Many papers have collected evidence for potential nonlinearity or instability of NKPCs as given in (2.1). Analyzing the period 2012–2016, Ciccarelli and Osbat (2017) find evidence for end of sample parameter instability, a potentially increased coefficient to slack and some evidence for increased inflation persistence. Using a time-varying parameter approach, Oinonen and Paloviita (2014) find evidence for an increased slack coefficient since 2012. Giannone *et al.* (2014) and Gross and Semmler (2019) find evidence for larger coefficients to slack when slack, e. g., measured by the unemployment rate, is big. Nonlinearity or instability of inflation persistence is documented by Ciccarelli and Osbat (2017) and Kanellopoulos and Koutrolis (2016), the latter providing some evidence that the coefficients to lagged inflation may themselves depend on lagged inflation. Colavecchio and Rubene (2020) document that inflation persistence may depend on the magnitude of exchange-rate changes.

Based upon OLS estimation of up to 42 variants, resulting from the up to seven slack and up to six imported inflation measures, of equation (2.1) for the euro area and the 15 considered member states, Figure 2.1 provides some indirect evidence concerning

[7] See, e. g., Mavroeidis *et al.* (2014) for a detailed discussion concerning different approaches to single equation estimation, referred to in that paper as limited information estimation, of NKPCs. That paper also includes an insightful discussion concerning expectations measures used in empirical NKPC analysis.

potential instability of the coefficients on lagged inflation.[8] The figure displays, in the form of Box-Whiskers plots, the *distribution* of the estimates of $\sum_{j=1}^{p^*} \beta_j$ for the euro area and the 15 considered member states over all estimated specifications. One noticeable observation is the considerable heterogeneity, both across specifications (at least for some countries) and across countries. The median estimate is given by 0.63 for the euro area and the smallest and largest country-specific median estimates are given by 0.22 for Slovakia and 0.81 for Lithuania.[9] The figure additionally displays the percentages of rejections of the null hypotheses of two tests performed for each jurisdiction for the up to 42 considered specifications. One null hypothesis corresponds to no long-run impact of lagged inflation, $\sum_{j=1}^{p^*} \beta_j = 0$, and the other one to unit root inflation persistence, conditional upon the other variables included, $\sum_{j=1}^{p^*} \beta_j = 1$.[10] The null hypothesis of no long-run inflation persistence is almost entirely rejected across all specifications, with some exceptions for Germany and Lithuania and is only rejected in about 30% of the specifications for Slovakia. The unit root null hypothesis is not rejected throughout for nine out of the fifteen member states, with the smallest rejection percentages for Lithuania (45%), Greece (50%) and Italy (69%). Against the background of low inflation rates over most of the sample period, the 2% inflation target and the well-known discussion concerning the aliasing of structural breaks as unit root type behavior (as put forward by Perron, 1989), the non-rejections of the unit root null hypothesis may be interpreted as indirect evidence of structural change in the Phillips curve, in particular also since time-varying means, found important, in, e. g., Bańbura and Bobeica (2020) and Cogley and Sbordone (2008), are hard to distinguish from random walk behavior (see, e. g., p. 98 in Teräsvirta *et al.*, 2010).

A more standard way of obtaining graphical evidence concerning potential structural change is to consider moving window estimates of the parameters in (2.1), as exemplified in Figure 2.2 for the euro area, Austria, Germany and Slovenia, including two lags of inflation and using the output gap and the annual growth rate of the import deflator as slack and imported inflation measures, respectively.[11] The figure displays results based

[8] For all but four countries all seven slack measures and all six imported inflation measures are available, leading to 42 Phillips curve specifications for these countries. For Cyprus, the Netherlands, Slovakia and Slovenia some slack and/or imported inflation measures are missing (see Table A.2 in Appendix A), reducing the number of Phillips curves estimated for these countries to 25, 21, 25 and 30, respectively. The lag orders p^* are chosen for each specification by minimizing the AIC criterion of Akaike (1974) with an upper bound of eight lags. In 90% of all specifications p^* is smaller than eight. When using the more conservative BIC of Schwarz (1978), p^* is smaller than eight in even 99% of all specifications.

[9] Across all countries, the smallest estimate is -0.01 for Slovakia and the largest is 1.04 for Lithuania.

[10] We test the unit root null hypothesis with the covariate augmented Dickey-Fuller-type test of Hansen (1995).

[11] Of course, Austria, Germany and Slovenia have first and foremost been selected as they represent

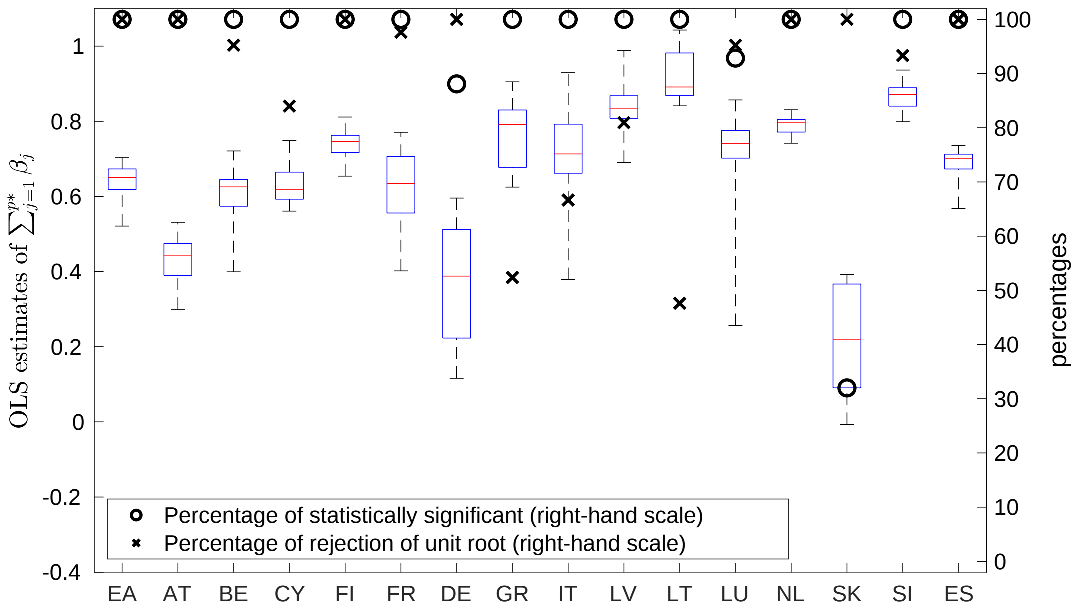

Figure 2.1: Box-whiskers plots for euro area and country-specific OLS estimates of $\sum_{j=1}^{p^*} \beta_j$ from (2.1) (left-hand scale) and percentages of rejections of null hypotheses that $\sum_{j=1}^{p^*} \beta_j$ equals zero or one, respectively (right-hand scale). Note: For each box, edges indicate the 25th and 75th percentiles of country-specific estimates, respectively. The central mark indicates the median and whiskers extend to the most extreme estimates. For the euro area and each member state, results are based on up to 42 combinations of the different slack and imported inflation measures.

on estimation windows of 16 quarters for the intercept, the sum of the coefficients to lagged inflation – as discussed in relation to Figure 2.1 – and to slack. Considering the first row of the figure and taking into account the overall variability of the coefficient estimates over the moving windows, it appears that with the exception of Austria the intercept declines, more so for Germany and Slovenia than for the euro area. For Austria, the intercept exhibits – similarly to (but slightly earlier than for) the euro area – a brief dip around 2016Q3. The long-run impact of lagged inflation, i. e., $\beta_1 + \beta_2$, as displayed in the second row of the figure, has gone down in the euro area and Austria, has remained relatively stable for Germany and seems to have gone up for Slovenia. Notwithstanding all the uncertainty due to the small estimation window – in addition to the uncertainty about the correct specification of NKPCs – it is remarkable that lagged inflation has a significant impact on inflation in Slovenia only. Considering the last row, it appears that the coefficient to slack has dropped sharply for the euro area and the three displayed member states around 2017 and 2018 and for all countries but Slovenia even entered

the countries of institutional affiliation of the authors. Nevertheless, however, the three countries differ in important aspects like size, economic structure and duration of European Union respectively euro area membership.

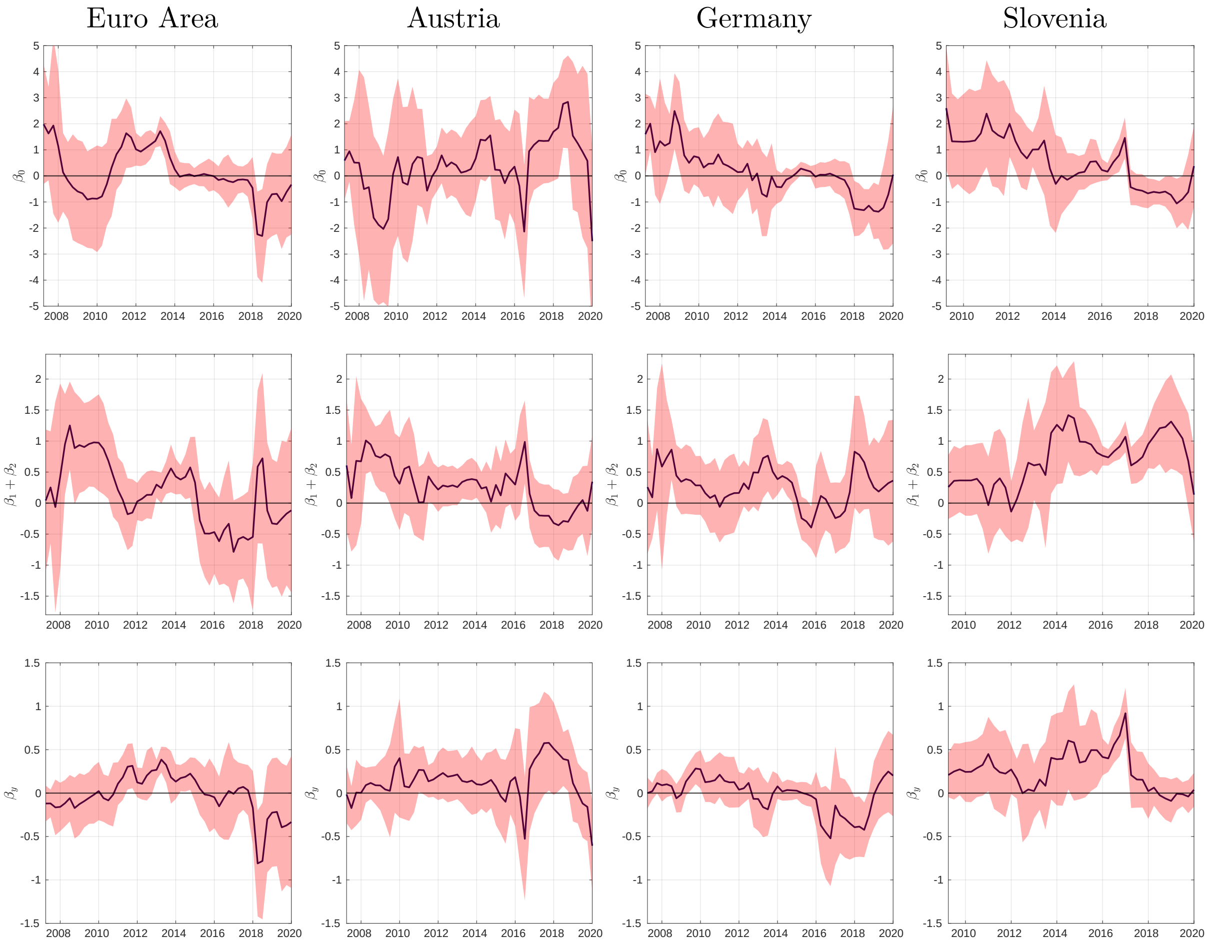

Figure 2.2: 16 quarter moving window parameter estimates of the open-economy hybrid new Keynesian Phillips curve (2.1) with two lags of inflation for the euro area, Austria, Germany and Slovenia. The top row shows the estimated intercepts β_0, the middle row the sum of the estimated parameters to lagged inflation $\beta_1 + \beta_2$ and the bottom row the estimated parameters to slack β_y. The shaded regions indicate plus/minus 1.96 standard deviation pointwise confidence intervals. Slack is measured by the output gap and imported inflation by the annual growth rate of the import deflator.

negative territory. After the drop, the coefficient remains at a lower level for the euro area, Germany and Slovenia, but recovered rapidly for Austria. To a lesser extent, we find these sharp drops around 2017 and 2018 also for the intercept in the euro area (in 2018Q2), Austria (2016Q3) and Slovenia (2017Q1).

The two figures are, of course, merely examples for the ample but hitherto scattered evidence for potential nonlinearities and instabilities in NKPCs. To address the question of nonlinearities and instabilities more systematically, the following subsection presents our approach to investigating nonlinearities and instabilities via (mis)specification testing.

2.2 Nonlinearities, Instabilities and Specification Testing

To motivate our specification testing approach, it is convenient to consider the variety of approaches used to test for or model nonlinearities and instabilities of Phillips curves under the semantic umbrella of "regime-switching". The simplest version of regime-switching is, of course, augmenting a linear regression by interacting some or all variables with dummy variables (in a Phillips curve context see, e. g., Barnes and Olivei, 2003; Gross and Semmler, 2019; Forbes *et al.*, 2021). One important issue is, whether in such approaches the dummy variables are constructed using ex ante specified thresholds, e. g., positive or negative slack, or whether the threshold parameter is itself considered to be unknown and needs to be estimated (see, e. g., Hansen, 2000). Moving from discrete-regimes via dummy-type variable approaches to "continuous regimes" leads to one popular interpretation of the smooth transition regression approach, see Bacon and Watts (1971) and Goldfeld and Quandt (1972), popularized in econometrics by Timo Teräsvirta and coauthors (see, e. g., Teräsvirta, 2004; Teräsvirta *et al.*, 2010). Considering regime-switching behavior not driven by (a function of) observables, but by an unobservable Markov chain, whose properties are allowed to depend on observables in more recent work, leads to Markov switching models. Early contributions are again Goldfeld and Quandt (1972, 1973). Markov switching models have been popularized in econometrics by the work of James Hamilton (1989, 1990), with one relatively early contribution that allows for endogenous switching being Kim *et al.* (2008). Another approach to model nonlinearities with a (semantic) focus on instability are time-varying parameter models of various types, either using random coefficient approaches (see, e. g., Oinonen and Paloviita, 2014, who use a state space formulation) or using coefficients that are modelled as deterministic functions of time.

Given the prominence of slack as a potential source of nonlinearity in the empirical Phillips curve literature, we illustrate the different approaches by also zooming in on slack. The starting point of a large part of the literature is in this case effectively given by the question whether an equation like (2.1) is well-specified, or whether there is evidence that an equation of the form:

$$\pi_t = \beta_0 + \sum_{j=1}^{p^*} \beta_j \pi_{t-j} + \beta_e \pi_t^e + + \beta_y y_{t-1} + G(y_{t-1}, \theta) y_{t-1} + \beta_m \pi_{t-2}^m + \varepsilon_t \tag{2.2}$$

provides a better fit, with the coefficient β_y to slack in (2.1) replaced by a non-constant function $\beta_y + G(y_{t-1}, \theta)$ of slack y_{t-1}.[12] In the simplest case of a dummy variable specifi-

[12]Considering the the function G depends on y_{t-1} is for brevity of exposition only. In principle any

cation this leads to $G(y_{t-1}, \theta) = \beta_{y,\mathrm{NL}} \mathbf{1}_{\{y_{t-1} > c\}}$, with $\mathbf{1}_{\{\cdot\}}$ denoting the indicator function. The threshold c is either set to one or several fixed values, e. g., in Forbes *et al.* (2021), or is also estimated. A (general form of a) logistic smooth transition alternative with transition variable y_{t-1} is given by $G(y_{t-1}, \theta) = \beta_{y,\mathrm{NL}} \left\{ \left(1 + \exp\left(-\gamma \prod_{k=1}^{K} (y_{t-1} - c_k)\right)\right)^{-1} - \frac{1}{2} \right\}$, with some identification conditions on the parameters c_k. In a Markov switching approach, the function $G(x_t, \theta)$ assumes two or more, in case of multiple regimes, values as a function of a Markov process $\{x_t\}$ that is either assumed to be independent of slack (exogenous switching) or is allowed to be correlated with slack (endogenous switching) and where θ specifies the transition probabilities between the two or more states and potentially the dependence between x_t and y_{t-1}. In this example, time-varying coefficient approaches lead to $G(y_{t-1}, \theta) = \beta_{y,t-1}$ with, e. g., a random walk coefficient sequence $\beta_{y,t-1} = \beta_{y,t-2} + \eta_{t-1}$, with η_t white noise, or as a deterministic function of time with $\beta_{y,t-1} = \beta(t)$, or $\beta_{y,t-1} = \beta\left(\frac{t}{T}\right)$, with T denoting sample size. The function $\beta(\cdot)$ is either parametrically specified or approximated by nonparametric estimation. The usual formulations of time-varying coefficients models consider time variation in the parameters to be independent of the explanatory variables, which is a similarity to a Markov switching approach with exogenous switching, or as a deterministic function of time.

The distinction between nonlinearity and instability is to a certain extent of semantic nature only, since most forms of parameter instabilities lead to nonlinear models. The "closer" the nonlinearity is related to structural change in parameters for which no economic modelling rationale and strategy can be found or is even considered, the more such changes are seen as parameter instabilities. Smooth transition regression models allow to exemplify this ambiguity nicely. If, e. g., the transition variable is time, i. e., $s_t = t$, the (corresponding) parameters are effectively modelled as a smooth function of time. This would mostly be interpreted as (evidence for) parameter instability rather than as a genuine nonlinear economic model describing inflation dynamics. If, however, the transition variable is lagged slack, then many would interpret this as evidence for a nonlinear impact of slack on inflation dynamics that requires further investigation of the economic mechanisms leading to this (empirically relevant) nonlinear effect. Thus, the favored semantic formulation will be case-specific. We abstain from semantic differentiation henceforth and typically simply refer to nonlinearities.

The scattered evidence across papers concerning sources and channels of nonlinearities suggests to address two questions systematically: First, which variable or variables should

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other variable or even unobserved latent variables could be present in G. The empirical analysis in the following section uses a large number of observable variables as s_t.

be considered to be sources of nonlinearities? In this respect the possibility that a variable not considered as regressor in the baseline specification drives nonlinearities needs to be considered. Second, how is the nonlinearity transmitted into inflation (dynamics)? From the already mentioned papers, e. g., Barnes and Olivei (2003) and Forbes *et al.* (2021) consider regime-switching behavior only via (domestic) slack measures, whereas Gross and Semmler (2019) consider specifications where, using the notation of (2.1), the entire vector of explanatory variables Z_t is subject to regime-switching change. We address these two issues by investigating a broad set of potential sources, i. e., variables that potentially generate nonlinearities, and a broad set of potential transmission channels. More precisely, we perform a large number of specification tests allowing for (i) a large number of potential variables driving nonlinearity and (ii) by interacting nonlinearity with different subsets of the regressors, $Z_{t,\mathrm{NL}}$ henceforth, contained in (2.1). Hereby we assume smooth transition type behavior:

$$\pi_t = Z_t'\beta + Z_{t,\mathrm{NL}}'G(s_t, \theta) + \varepsilon_t, \tag{2.3}$$

where $G(s_t, \theta) = \beta_{\mathrm{NL}} \left(\left(1 + \exp\left(-\gamma \prod_{k=1}^{K}(s_t - c_k)\right)\right)^{-1} - \frac{1}{2} \right)$. The variable s_t denotes the so-called transition variable that is the source of nonlinearity. The nonlinear impact of s_t on inflation, modelled via its interaction with $Z_{t,\mathrm{NL}}$, is referred to as channel. In our analysis we consider as $Z_{t,\mathrm{NL}}$ different subsets of Z_t, but in principle, of course, $Z_{t,\mathrm{NL}}$ need not be a subset of Z_t. The choices of the sources s_t are discussed in the following subsection. A popular specification testing approach that we also follow here replaces the above unknown function $\left(1 + \exp\left(-\gamma \prod_{k=1}^{K}(s_t - c_k)\right)\right)^{-1} - \frac{1}{2}$ by a Taylor approximation.[13] This leads to the following auxiliary regression:

$$\pi_t = Z_t'\phi_0 + \sum_{j=1}^{q} \left(Z_{t,\mathrm{NL}} s_t^j\right)' \phi_j + \varepsilon_t^*. \tag{2.4}$$

Under the null hypothesis that (2.1) is well-specified it holds that $\phi_1 = \cdots = \phi_q = 0$, $\phi_0 = \beta$ and $\varepsilon_t^* = \varepsilon_t$, such that the LM-type test statistic for $\phi_1 = \cdots = \phi_q = 0$ is asymptotically chi-squared distributed.[14]

[13] Resorting to auxiliary regressions overcomes, at the expense of using an approximation, the problem that some nuisance parameters are unidentified in (2.3) under the null hypothesis of linearity – or present only under the alternative of nonlinearity. This type of problem has been studied in detail in Davies (1977, 1987), see also Luukkonen *et al.* (1988) or Teräsvirta *et al.* (2010, Chapter 5).

[14] Note for completeness that there are certain constellations in which tests using $q = 1$ can be (immediately) seen to result in trivial power, e. g., in case of a regression with an intercept and one regressor only in Z_t, with the transition variable equal to this regressor and with $Z_{t,\mathrm{NL}} = 1$. Furthermore, if an intercept is included in Z_t and s_t is an element of Z_t, then the intercept needs to be excluded in $Z_{t,\mathrm{NL}}$ to avoid multi-collinearity in (2.4). These issues are taken into account in our analysis and we do not

When taken at face value, the employed testing strategy is geared towards the alternative of smooth transition regression models, but it represents, of course, also approximate auxiliary regression tests in a Ramsey (1969) RESET spirit against the other discussed alternatives. As an example, a switching regression with, as before $G(y_{t-1}, \theta) = \beta_{y,\mathrm{NL}} \mathbf{1}_{\{y_{t-1}>c\}}$ can be seen as boundary or limit case of $G(y_{t-1}, \theta) = \beta_{y,\mathrm{NL}} \frac{1}{1+\exp(-\gamma(y_{t-1}-c))}$ for $\gamma \to \infty$.[15] In a similar spirit, Hansen (2000, Section 5) contains a discussion concerning the usage of the type of auxiliary regression-based test we use when testing the null hypothesis of linearity against threshold-type alternatives. Approximate test statistics based on (2.4) will exhibit the higher power against an unknown nonlinear function, the better this unknown nonlinear function is approximated by the auxiliary regressors in (2.4). The approximation quality will depend not least on the choice of s_t.[16] As an example, if the data are generated by a model with time-varying parameters occurring only for some of the regressors, then an approximation test based on including these regressors in $Z_{t,\mathrm{NL}}$ and using $s_t = t$ will be more powerful than a test based on including only other variables that are not interacted with time-varying coefficients in the auxiliary regressors. The performance will be even poorer in case the regressors included in the auxiliary regressor terms are orthogonal to the variables that are interacted with time-varying coefficients. Our battery of specification tests based on a variety of transition variables and regressors $Z_{t,\mathrm{NL}}$ allows to pick up evidence in different "directions" that will, in subsequent work, serve as starting points for estimating appropriate nonlinear models of the variety preferred by the researcher, potentially in combination with first performing tailor-made tests of linearity against the preferred nonlinear alternative.

2.3 Sources and Channels

As already mentioned in the introduction and the previous section, this subsection provides and discusses the list of altogether nine variables that we consider as potential sources of nonlinearities of the Phillips curve. In line with the "classification" presented in the introduction, we group the sources in cyclical domestic drivers, imported inflation, short-term interest rates and long-term structural factors. We also consider time itself as a source of nonlinearity, used as a "reduced form" or "non-targeted" approach to testing for nonlinearities (or structural change).

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comment upon these well-known technical issues any further.

[15] This argument has in fact a prominent role in Bacon and Watts (1971) and Goldfeld and Quandt (1972).

[16] More precisely the issue is the (asymptotic) dependence between the unknown function and the auxiliary regressors in (2.4), i. e., whether the least squares projection of the unknown function on the auxiliary regressors in (2.4) leads asymptotically to non-zero coefficients or not.

It is important to stress that the terminology, sources and channels, is intended to simplify and structure the subsequent discussion. Our statistical analysis is *inspired* by the literature, but does not necessarily directly refer to "economically meaningful" channels and sources. However, our findings do shed light on the relative importance of potentially important further considerations of NKPC-type relationships, both from an empirical perspective, but ultimately also in terms of extending the underlying theory toolkit to accommodate mechanisms that may have been uncovered with empirical reduced form analysis. In this respect our analysis has to be interpreted as a systematic look – through the lens of our approximation-based misspecification testing – where more attention should potentially be put on trying to understand inflation behavior. The terminology channel and source should, thus, not be taken too literally, but merely interpreted as a semantic structuring device.

Let us start by considering the two key domestic cyclical drivers of inflation, slack and (lagged) inflation. In line with the discussion in the previous section, slack can be either seen as a source of nonlinearity, or a channel through which nonlinearity acts or both.[17] The literature provides several references that investigate a potentially nonlinear impact of slack as a source on slack as a channel itself (see, e. g., Barnes and Olivei, 2003; Ciccarelli and Osbat, 2017; Giannone *et al.*, 2014; Gross and Semmler, 2019; Smets, 2010), i. e., $s_t = Z_{t,\mathrm{NL}} = y_{t-1}$. A potentially high impact of very low slack on inflation reflects price-setting behavior of capacity constrained firms (see, e. g., Macklem, 1997), with price changes more prominent during boom periods where firms operate at or near full capacity. To a similar end, Daly and Hobijn (2014) argue that downward nominal (wage) rigidities may imply that the effect of slack on inflation may be smaller for large slack. Forbes *et al.* (2021) present evidence that the impact of slack on inflation may depend upon lagged inflation, potentially in addition to slack itself, i. e., $s_t = \pi_{t-1}$ and $Z_{t,\mathrm{NL}} = y_{t-1}$. This combination can also be motivated from a menu-cost perspective (see, e. g., Gertler and Leahy, 2008; Costain *et al.*, 2019), where low inflation (in a world of nominal rigidities) reduces the frequency of price changes with the effect of slack on inflation depending upon the frequency of price changes. Longer periods of inflation over- or undershooting the inflation objective might lead to a higher dependence of inflation on past inflation compared to its dependence on expected inflation, see also Ciccarelli and Osbat (2017).[18] As already discussed in Section 2.1, previous values of inflation could also affect the impact

[17]With the notation of the previous section, thus either $s_t = y_{t-1}$ or $Z_{t,\mathrm{NL}} = y_{t-1}$ or contains y_{t-1}. With $s_t = y_{t-1}$, of course, the next question is with which variables, i. e., channel $Z_{t,\mathrm{NL}}$, slack interacts. Clearly, the literature points to specific candidates of $Z_{t,\mathrm{NL}}$. However, without prior knowledge the first natural choice would be $Z_{t,\mathrm{NL}} = Z_t$.

[18]In our notation this refers to $s_t = \pi_{t-1}$ and $Z_{t,\mathrm{NL}}$ either $[\pi_{t-1}, \ldots, \pi_{t-p^*}]'$, π_t^e or both.

of past inflation on current inflation (see, e. g., Kanellopoulos and Koutroulis, 2016), but the impact of past inflation on current inflation might also depend on the magnitude of exchange-rate changes, which is one of our imported inflation measures (see, e. g., Colavecchio and Rubene, 2020).

Brand *et al.* (2018) discuss the possibility that protracted periods of economic distress might alter household (and firm) behavior, which might in turn exert downward pressure on long-term inflation and change the impact of expected inflation on price-setting behavior ($s_t = y_{t-1}$ and $Z_{t,\mathrm{NL}} = \pi_t^e$). External cost-push shocks, with the resulting real exchange rate changes, lead to changing import demand and therefore impact the relative importance of external and domestic drivers of inflation. The importance of this mechanism is investigated by using $s_t = \pi_{t-2}^m$ and $Z_{t,\mathrm{NL}}$ either π_{t-2}^m, y_{t-1} or both. Short-term or policy interest rates like the (quarterly) EONIA rate, contain important information on the expected macroeconomic environment (see, e. g., Angelini *et al.*, 2019; Rostagno *et al.*, 2021; Eser *et al.*, 2020; Jarociński and Karadi, 2020), leading to, taking the mechanisms described in these papers together, $s_t = \text{EONIA}$ and $Z_{t,NL} = 1$, $[\pi_{t-1}, \ldots, \pi_{t-p^*}]'$, π_t^e, or combinations thereof and y_{t-1}.

Long-term inflation expectations (π_t^{e5}), demographic trends (AGE), the level of global value chain integration (OPEN), or the level of digitalization (DESI) have also been found to impact inflation dynamics. For example, Bańbura and Bobeica (2020) find that changes in long-term inflation expectations affect trend inflation. Moreover, an ageing population with a consequently increasing supply of savings and an implied drag on the natural rate of interest may lead to *ceteris paribus* lower inflation rates (see, e. g., Bobeica *et al.*, 2017; Ciccarelli and Osbat, 2017; Lis *et al.*, 2020). To the contrary, Juselius and Takáts (2016) argue that population ageing may in fact lead to increasing consumption and may thus exhibit positive impact on long-term inflation trends. The impact of ageing, as well as the exact transmission mechanism of ageing on inflation dynamics is thus less clear than one might first think. Related to external cost-push shocks (modeled by imported inflation measures) and potentially magnifying the importance of such shocks are the potential impacts of increasing integration in global value chains on inflation dynamics (see, e. g., Eser *et al.*, 2020; Forbes, 2020). According to this logic, the level of integration in global value chains, measured here by the sum of exports and imports divided by GDP, might reduce the importance of slack for inflation and increase the importance of global or external factors. With respect to digitalization, e. g., Weidmann (2018) touches upon a variety of aspects, exemplifying that digitalizaton may entail both disinflationary (increased competition due to lower information and transaction costs) as well as inflationary (increased market power due to increasing returns originating from, e. g., network externalities) effects. Using $s_t = t$ directly leads to tests for structural change that capture time variation in the effects of the channels considered on inflation. Although time-varying effects play an important role in the literature (see, e. g., Bańbura and Bobeica, 2020; Bobeica and Jarociński, 2017; Ciccarelli and Osbat, 2017; Cogley and Sbordone, 2008; Oinonen and Paloviita, 2014) using time as transition variable – in contrast to economic variables – does not directly link potential rejections of linearity to economic mechanisms. However, our list of selected variables is not exhaustive and thus structural change may well be due to other, non-considered, variables with time potentially picking up at least some of the induced nonlinearity. We summarize our list of the nine potential sources together with exemplary references in Table 2.1, while Table 2.2 summarizes the nine corresponding channels through which theses sources potentially effect inflation.[19]

The above discussion related to sources and corresponding channels has highlighted some combinations of – in our notation – s_t and $Z_{t,\mathrm{NL}}$ that are closely related to important mechanisms described in the literature. For completeness, however, we analyze the results for the full set of combinations of s_t as given in Table 2.1 and $Z_{t,\mathrm{NL}}$ as given in Table 2.2. In this respect note that we consider nested channels that allow to potentially differentiate clearer between possible mechanisms described in the literature. To clarify the argument, consider the following example related to the above discussion about external cost-push shocks and their impacts. Using as $Z_{t,\mathrm{NL}}$ the variables y_{t-1}, π^m_{t-2} or $[y_{t-1}, \pi^m_{t-2}]'$ allows to gauge the relative importance of slack and imported inflation on inflation. When considering, e. g., $s_t = y_{t-1}$, 43% of the tests reject for $Z_{t,\mathrm{NL}} = [y_{t-1}, \pi^m_{t-2}]'$, 41% for $Z_{t,\mathrm{NL}} = y_{t-1}$ and 30% for $Z_{t,\mathrm{NL}} = \pi^m_{t-2}$, referring here to aggregate numbers considering the euro area and all 15 member states, slack and imported inflation measures. The detailed discussion in the following section shows that $Z_{t,\mathrm{NL}} = y_{t-1}$ leads to higher rejection percentages than $Z_{t,\mathrm{NL}} = \pi^m_{t-2}$ not only for $s_t = y_{t-1}$, but for all sources.[20] Thus, it appears that understanding the impact of slack on inflation better, in particular its relation to potential nonlinearities of NKPCs, is more important than obtaining a better understanding of the impact of imported inflation. However, as we will see in Table 3.1

[19] To be clear, our terminology of sources and channels has to be interpreted modestly. In the end we only test whether a combination of source s_t interacted with some other variables collected in a channel $Z_{t,\mathrm{NL}}$ leads to rejections of the null hypothesis of linearity against adding the corresponding interaction terms. Whilst this is, and this is why we do it, informative about potential (economic) mechanisms that exert changing impact on inflation dynamics, this is not tantamount to uncovering new structural economic mechanisms. It may, however, inspire in the best case the development of models that capture the mechanisms flagged by our misspecification testing approach.

[20] The overall rejection rates for $Z_{t,\mathrm{NL}} = y_{t-1}$ and $Z_{t,\mathrm{NL}} = \pi^m_{t-2}$ are given by 30% and 22%, respectively.

Table 2.1: Sources

s_t	Describing	Exemplary references
y_{t-1}	slack or economic activity (up to seven measures)	Barnes and Olivei (2003), Brand *et al.* (2018), Ciccarelli and Osbat (2017), Daly and Hobijn (2014), Giannone *et al.* (2014), Gross and Semmler (2019), Macklem (1997), Smets (2010)
π_{t-1}	inflation inertia	Ciccarelli and Osbat (2017), Costain *et al.* (2019), Gertler and Leahy (2008), Kanellopoulos and Koutroulis (2016)
π^m_{t-2}	imported inflation (up to six measures)	Colavecchio and Rubene (2020)
EONIA	short-term or policy interest rates	Eser *et al.* (2020), Jarociński and Karadi (2020), Rostagno *et al.* (2021)
π^{e5}_t	long-term inflation expectations	Bańbura and Bobeica (2020)
AGE	demographic trends	Bobeica *et al.* (2017), Ciccarelli and Osbat (2017), Juselius and Takáts (2016), Lis *et al.* (2020)
OPEN	level of global value chain integration	Eser *et al.* (2020), Forbes (2020)
DESI	level of digitalization	Weidmann (2018)
t	"unmodelled" structural change	Bańbura and Bobeica (2020), Bobeica and Jarociński (2017), Ciccarelli and Osbat (2017), Cogley and Sbordone (2008), Oinonen and Paloviita (2014)

Note: Table A.1 in Appendix A describes the variables in more detail.

in Section 3.2, the relative importance of $Z_{t,\mathrm{NL}} = \pi^m_{t-2}$ for explaining nonlinearities of the Phillips curve varies across countries. For Germany, Latvia and Lithuania this channel accounts for less than five percent of all nonlinearities, whereas it accounts for more than ten percent of all nonlinearities for Belgium, Cyprus, France, Italy and Slovakia. This also indicates that there is no direct link between a potential nonlinear impact of imported inflation on the Phillips curve and the size of the economy.

Table 2.2: Channels

Channel	$Z_{t,\mathrm{NL}} =$	Capturing changing
intercept	1	(conditional) mean
lagged inflation	$[\pi_{t-1}, \ldots, \pi_{t-p^*}]'$	impact of past inflation
expected inflation	π_t^e	impact of 1y inflation expectations
lagged or expected inflation	$[\pi_{t-1}, \ldots, \pi_{t-p^*}, \pi_t^e]'$	impact of past or expected inflation
long-run inflation mean	$[1, \pi_{t-1}, \ldots, \pi_{t-p^*}, \pi_t^e]'$	long-run mean
slack	y_{t-1}	impact of slack or economic activity (up to seven measures)
imported inflation	π_{t-2}^m	impact of imported inflation (up to six measures)
slack or imported inflation	$[y_{t-1}, \pi_{t-2}^m]'$	impact of slack or imported inflation
unspecified	Z_t	parameters in the Phillips curve

Note: Table A.1 in Appendix A describes the variables in more detail.

3 Results

Considering for the euro area and its member states all combinations of channels, sources and available slack and imported inflation measures leads to in total 49,005 linearity tests.[21] For $q = 1$, almost a third (32.54%) of these tests reject the null hypothesis that (2.1) is well-specified at the nominal 5% level.[22] However, rejection rates for the euro area and its member states are heterogeneous, ranging from 7% for Cyprus to 56% for the euro area. In addition, rejection rates vary considerably across channels, sources and slack and imported inflation measures. To account for these different dimensions of heterogeneities, this section first zooms in onto differences across channels and sources, then focuses on cross-country differences and finally sheds light on the implications of using different slack and imported inflation measures on the results.

[21] Please note that in this section the term “slack” refers to slack and economic activity, compare the discussion in Footnote 5.

[22] Setting $q = 3$ and thus including additional nonlinear terms in the auxiliary regression (2.4) yields an only slightly larger overall rejection rate of 34.87% at the cost of increasing the number of parameters to be estimated considerably. To avoid overfitting for larger vectors $Z_{t,\mathrm{NL}}$, we thus focus on the results for $q = 1$.

3.1 Differences Across Channels and Sources

Figure 3.1 displays the channel-specific rejection rates aggregated over all sources, economies and slack and imported inflation measures as horizontal lines. Potentially not surprising, the largest rejection rate (42%) occurs for $Z_{t,\text{NL}} = Z_t$. This case allows interactions between the transition variable and each variable included in the linear Phillips curve in (2.1). Reducing the number of interactions by considering channels with less variables is likely to decrease the rejection rates, however, we find that rejection rates corresponding to channels including more variables are not generally larger than those corresponding to channels with less variables. After the unspecified channel, the long-run inflation mean leads to the largest rejection rate (38%), whereas the smallest rejection rate (22%) occurs for the imported inflation channel. Thus, understanding variations in the long-run inflation mean appears to be more important for explaining potential nonlinearities of the Phillips curve than obtaining a better understanding of the impact of imported inflation on domestic inflation (22%).

The third largest rejection rate occurs for the intercept (35%) and is only seven percentage points smaller than the rejection rate corresponding to the unspecified channel. The rejection rates for the remaining five channels lie all around 30%. The nested structure of the channels allows to draw at least two additional conclusions. First, variations in the intercept appear to be more important for explaining variations in the long-run inflation mean than potentially unstable effects of forward and/or backward looking inflation on current inflation. Second, as $Z_{t,\text{NL}} = y_{t-1}$ and $Z_{t,\text{NL}} = [y_{t-1}, \pi^m_{t-2}]'$ lead to similar rejection rates, with rejection rates for $Z_{t,\text{NL}} = \pi^m_{t-2}$ being considerably smaller, variations in the effect of slack on inflation seem to be more important than variations in the effect of imported inflation.

Having assessed the importance of the different channels aggregated over all sources, the next step is to identify the most important sources of nonlinearities in the NKPC aggregated over all channels. Analogous calculations to those above reveal that the in-sample declining EONIA rate leads to the highest rejection rate (47%).[23] The second largest rejection rate (41%) corresponds to lagged slack. Notably, both the EONIA rate and lagged slack lead to larger rejection rates than the deterministic time trend (38%). That is, choosing either of the two economic sources improves the approximation quality

[23]In relation to the discussion in the beginning of Section 2.3, this finding should not be taken as evidence that the EONIA rate is literally the most important source of nonlinearities in the NKPC because of two reasons: First, other variables not taken into account might play an even more important role. Second, the testing approach does not allow to distinguish between highly correlated variables in the sense that highly correlated sources lead to similar rejection rates.

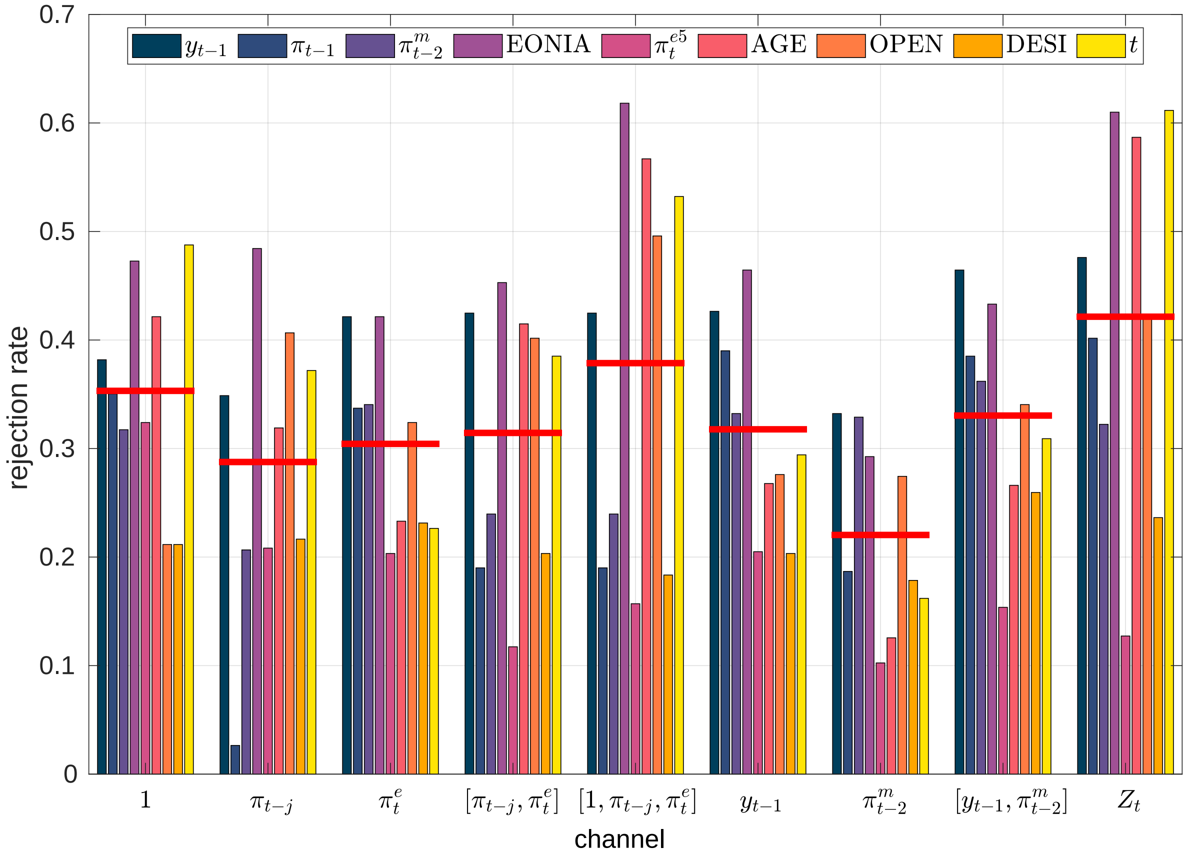

Figure 3.1: Rejection rates for all combinations of channels and sources. Notes: The symbol π_{t-j} is shorthand notation for $[\pi_{t-1}, \ldots, \pi_{t-p^*}]'$. Heights of horizontal lines are the average heights of the corresponding nine sub bars and represent the overall rejection rates for the different channels.

of the auxiliary regression relative to choosing $s_t = t$. Thus, especially the EONIA rate and lagged slack might account for time-varying effects found in previous studies. Two other important sources of nonlinearites of the Phillips curve are demographic trends and the level of global value chain integration (around 35%). Although the two variables account for slightly fewer rejections than the deterministic time trend, the relative large rejection rates point towards important effects of the age structure and the level of global-value chain integration on inflation dynamics.[24] Moreover, imported and lagged inflation lead to a rejection rate of 30% and 27%, respectively, while the digitalisation indicator leads to a rejection rate of 21%. Especially in light of the large rejection rates for the EONIA rate and lagged slack, long-term inflation expectations (18%) seem to be rather unimportant to explain nonlinearities of the Phillips curve.

Figure 3.1 also allows to analyze the rejection rates for each combination of the con-

[24] In general, results for demographic trends are very similar to the results for the deterministic time trend, stemming from the fact that both variables are slowly varying and highly correlated. However, on the country-level there are interesting patterns between country-specific rejection rates and their population's age structure. The next subsection discuss these findings in detail.

sidered channels and sources aggregated over the euro area and its member states and the different slack and imported inflation measures. The following observations are particularly noteworthy. First, for each channel the source leading to the highest rejection rate is either the EONIA rate, slack or the deterministic time trend. Second, for each channel except $Z_{t,\text{NL}} = \pi^m_{t-2}$, the EONIA rate leads either to the largest or second largest rejection rate.[25] Third, the large rejection rate for the combination $s_t = y_{t-1}$ and $Z_{t,\text{NL}} = y_{t-1}$ is in line with the literature finding a potentially nonlinear impact of slack on inflation. However, the effect of slack on inflation seems to also depend on lagged inflation and the EONIA rate. Thus, the result point in the same direction as the results in Forbes *et al.* (2021), implying that studies focusing only on threshold effects of lagged slack on inflation may miss interesting and potentially important patterns. Fourth, the EONIA rate is also the main source for changes in the long-run inflation mean. The corresponding rejection rate of 62% is the highest rejection rate across all combinations of channels and sources. Maybe surprisingly, the rejection rate for $Z_{t,\text{NL}} = \pi_{t-j}$ in conjunction with $s_t = \pi_{t-1}$ is almost zero, indicating that the effect of lagged inflation on inflation does not vary with the level of past inflation. Instead, it appears that this effect is mainly driven by the EONIA rate, with a rejection rate of almost 50%. Finally, Figure 3.1 reveals that the most important source for an unstable intercept is the deterministic time trend, with a rejection rate of almost 50%. This result is consistent with the growing evidence in the forecasting literature, emphasizing the significance of a time-varying intercept for accurate inflation predictions (see, e. g., Bańbura and Bobeica, 2020). It might also explain some of the (near-)unit root values reported in Figure 2.1, as processes with time-varying means are often difficult to distinguish from random walks (Teräsvirta *et al.*, 2010, p. 98). However, as the results are aggregated over the euro area and its member states, it is too early to draw these conclusions. The next subsection therefore analyzes country-specific results.

3.2 Differences Across Countries

Figure 3.2 illustrates the rejection rates for the euro area and its member states. The rejection rates are heterogeneous across member states ranging from 7% for Cyprus to 48% for Belgium. However, the largest rejection rate (56%) is observed for the euro area. Thus, cross-country aggregation increases rather than decreases the amount of nonlinearities of the Phillips curve. Except Cyprus, all member states have rejection

[25]The main sources of nonlinearities in $Z_{t,\text{NL}} = \pi^m_{t-2}$ are slack and imported inflation itself, indicating that the effect of imported inflation on domestic inflation depends on both economic activity or slack and the level of imported inflation.

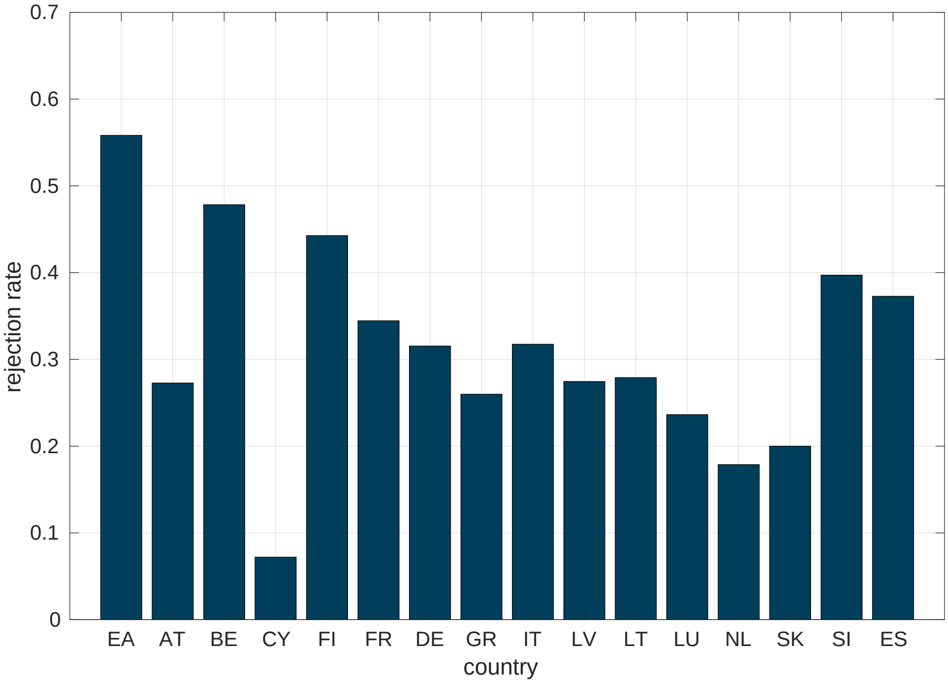

Figure 3.2: Country-specific rejection rates

rates of at least 18%, indicating that nonlinearities of the Phillips curve are a euro area wide phenomenon.[26] Besides the euro area, there are four member states with rejection rates close to or above 40%, namely Belgium, Finland, Slovenia and Spain. For France, Germany and Italy linearity is rejected in around a third of all tests. Besides Cyprus, the countries with the most stable Phillips curve are the Netherlands and Slovakia, with 18% respectively 20% of all tests rejecting the null hypothesis of linearity of the Phillips curve specification for these countries.

It is worth mentioning that there seem to be no directly visible patterns relating the rejection rates to, e. g., the size of the economy. We thus proceed with a more detailed analysis of the relative importance of different channels and sources within the euro area and each of its member states. Table 3.1 reports the relative contribution of each channel (Panel A) and each source (Panel B) to the country-specific rejection rates. Panel A highlights four interesting features. First, either the intercept or the long-run inflation mean is the most important channel – ignoring the unspecified channel $Z_{t,\mathrm{NL}} = Z_t$ – for

[26]For Cyprus and Slovakia the sample ends in 2017Q2 and 2017Q4, respectively, whereas for the other countries data is available at least until 2019Q4, compare Table A.2 in Appendix A. Rejection rates for the euro area and its member states are qualitatively similar when rerunning the analysis with all samples forced to end in 2017Q2, compare Figure B.1 in Appendix B. In this case, however, although still important, the EONIA rate is less dominant in explaining nonlinearities. Its overall rejection rate reduces from 47% to 41% and its importance for nonlinearities in, e. g., the intercept and the slack channel reduces from 47% to 38% for the intercept and from 46% to 38% for the slack channel. Thus, it appears that the importance of the EONIA rate for explaining nonlinearities of the Phillips curve has increased since 2017.

the euro area and all member states except Belgium and Greece.[27] Second, $Z_{t,\text{NL}} = \pi^m_{t-2}$ appears to be the most unimportant channel for five countries including the euro area and Germany. Third, every channel, except $Z_{t,\text{NL}} = Z_t$ and $Z_{t,\text{NL}} = y_{t-1}$, is at least for one country the most unimportant channel. Fourth, for the euro area, all channels account for approximately the same amount of rejections. This is in contrast to the results for the euro area member states, where often a few channels already account for a large share of rejections. Thus, cross-country aggregation seems to accumulate nonlinearities in the different channels.

Panel B reveals that, in contrast to the most important channel, the most important source seems to be highly country-specific. Interestingly, although the EONIA rate is the most important source of nonlinearities aggregated over the euro area and its member states, on the country-level it is most important for Germany (together with the level of digitalization), Lithuania and Slovenia only. Three other variables are the most important source of nonlinearities for three countries, namely slack (for Finland, France and Luxembourg), the level of global value chain integration (for Belgium, Greece and Spain) and the level of digitalization (for Cyprus, again Germany and Slovakia). Noteworthy, demographic trends are the most important source of nonlinearities of the Phillips curve for the Netherlands, accounting for almost 30% of all rejections, which is the second largest share over all countries and sources. The Dutch median age is not outstanding, however, the Netherlands face the third largest increase in the share of the population aged 65 years or over between 2011 and 2021 among all euro area member states.[28] In this light, the results point towards effects of an increasing elderly population in the Netherlands on the stability of its Phillips curve.[29] It is also worth pointing out that the level of digitalization and long-term inflation expectations are the most unimportant sources for six and five countries, respectively. Moreover, although $Z_{t,\text{NL}} = \pi^m_{t-2}$ is the most unimportant channel for five countries, imported inflation is never the most unimportant source for any country.

We now turn to country-specific rejection rates for the 81 different combinations of channels and sources. To illustrate the results, we generate for each country a 9×9

[27] The unspecified channel is the most important channel for Germany, Lithuania, Luxembourg and Slovenia.

[28] For the median age see Eurostat(a) (accessed: March 21, 2022) and for the increase in the share of the elderly population see Eurostat(b) (accessed: March 21, 2022).

[29] According to the Eurostat references cited in Footnote 28, Italy has the largest median age of all euro area countries and Finland has the highest increase in the share of the population aged 65 years or over between 2011 and 2021. The discussion below provides some evidence that for Italy, Finland and the Netherlands the large, respectively increasing, share of the elderly population might affect the stability of their Phillips curves.

matrix, with each cell displaying the rejection rate for a specific combination of channel and source. To ease exposition of the results, we color the cells of the matrix, with darker shades corresponding to larger rejection rates. Figure 3.3 provides the results for the euro area, Austria, Germany and Slovenia and Figures B.2–B.4 in Appendix B provide the results for the remaining countries.

As pointed out above, either the intercept or the long-run inflation mean is the most important channel (other than $Z_{t,\text{NL}} = Z_t$) for the euro area and all member states except Belgium and Greece. The most important channels for Belgium and Greece are $Z_{t,\text{NL}} = \pi_t^e$ and $Z_{t,\text{NL}} = [\pi_{t-1}, \ldots, \pi_{t-p^*}]'$, respectively. We are now in the position to identify for the euro area and each member state separately the main source of nonlinearities entering the Phillips curve through the most important channel. For some countries there is more than one source that leads to the highest rejection rate in combination with the country's most important channel. Sometimes, the corresponding rejection rate is even equal to one, meaning that the test rejects the null hypothesis of a well-specified country-specific Phillips curve (2.1) for all combinations of slack and imported inflation measures.[30] Allowing for multiple winners per country, the figures reveal that for six countries (euro area, Austria, Finland, Italy, the Netherlands and Spain) demographic trends are the main source of nonlinearities entering the Phillips curve through the countries' most important channel, followed by the level of integration in global-value chains (for Belgium, Greece, Luxembourg and Spain), the level of digitalization (for the euro area, Belgium, Germany and Slovakia) and the deterministic time trend (for the euro area, Austria, France and Spain). For three countries (Latvia, Luxembourg and Slovenia) lagged inflation is the main source of nonlinearities entering the Phillips curve through the countries' most important channel, followed by the EONIA rate for two countries (Germany and Slovenia) and long-term inflation for one country (Cyprus).[31]

The figures further allow to verify whether time-varying intercepts indeed explain the (near-)unit root values detected in Figure 2.1 especially for Lithuania, Greece and Italy, compare also the discussion in the end of Section 3.1. Figure B.3 in Appendix B reveals that time-varying intercepts are very unlikely to explain the small unit-root rejection rates for Lithuania and Greece. Instead, the main source of changes in the intercept for

[30]These combinations may be particularly important for further considerations of NKPC-type relationships from an empirical perspective and potentially also in terms of extending underlying economic theory to accommodate corresponding mechanisms.

[31]Noteworthy, demographic trends are the main source for nonlinearities in the most important channel for Italy (which has the highest median age) and Finland and the Netherlands (which have the highest and third highest increase in the share of the elderly population), compare the discussion in Footnotes 28 and 29.

the two countries is past inflation. For Italy, on the other hand, deterministic changes in the intercept could indeed explain the small unit-root rejection rate, but changes in the intercept could as well be driven by demographic trends and long-term inflation expectations.

Finally, we analyze the importance of different combinations of channels and sources for the euro area, Austria, Germany and Slovenia in more detail. Focusing on the shades of the cells in Figure 3.3 it appears that the matrices for Austria, Germany and Slovenia are rather "sparse" in the sense that many cells have a bright shade (signaling small rejection rates for the corresponding combinations of channels and sources) and only a few cells have a dark shade (signaling high rejection rates).[32] In contrast, the matrix for the euro area is "dense" in the sense that many cells have a darker shade. The aggregating effects observed at several other occasions in this section thus also prevail when considering the different combinations of channels and sources. Notably, for Austria, there is no combination of channel and source that seems to be particularly important. The largest rejection rates (67%) occur when interacting the deterministic time trend or demographic trends with the intercept or the deterministic time trend with $Z_{t,\mathrm{NL}} = \pi_t^e$. For Germany and Slovenia, however, there are a few combinations of channels and sources leading to rejection rates above 90%. For Germany, most of these high rejection rates correspond to the EONIA rate and the channels containing lags of inflation, or occur when interacting the long-run inflation mean with the EONIA rate, demographic trends, the level of digitalization or the deterministic time trend. The EONIA rate plays an important role for Slovenia as well, affecting all but two channels ($Z_{t,\mathrm{NL}} = \pi_t^e$ and $Z_{t,\mathrm{NL}} = \pi_{t-2}^m$). In contrast to Germany, however, also the level of integration in global value chains seems to be an important source of nonlinearities in the Slovenian Phillips curve in all channels containing backward or forward looking components of inflation.

Turning again to the euro area, there are many combinations of channels and sources leading to rejection rates equal to one, with all of them occurring either for the EONIA rate, demographic trends, the level of digitalization or the deterministic time trend as the source and – taking into account the nested structure of the channels – especially in combination with the intercept and the long-run inflation mean. In particular, the results confirm the presumption that the intercept of the euro area Phillips curve is unstable, stressing the importance to allow for a time-varying intercept to, e. g., improve the euro area Phillips curve's forecasting performance (Bańbura and Bobeica, 2020). However, time is not the only potential source of an unstable intercept. Also demographic trends

[32] Matrices for the remaining euro area member states are also "sparse".

Table 3.1: Relative contributions (in %) of channels and sources to country-specific rejection rates

	EA (0.56)	AT (0.27)	BE (0.48)	CY (0.07)	FI (0.44)	FR (0.34)	DE (0.32)	GR (0.26)	IT (0.32)	LV (0.27)	LT (0.28)	LU (0.24)	NL (0.18)	SK (0.20)	SI (0.40)	ES (0.37)
Panel A: Channels																
1	**12.85**	**15.95**	10.02	**23.29**	2.32	**15.36**	8.39	9.05	**16.94**	6.42	11.49	12.06	**22.37**	**20.49**	**13.78**	**17.03**
π_{t-j}	11.80	9.59	7.74	8.22	13.08	7.59	9.51	**18.44**	5.28	15.10	8.75	3.48	12.17	3.70	10.36	8.12
π_t^e	12.01	14.22	**16.04**	4.79	14.87	12.29	5.87	6.00	9.54	10.28	9.69	9.08	8.22	**20.49**	4.66	2.21
$[\pi_{t-j}, \pi_t^e]$	12.01	7.11	7.31	6.16	12.28	6.91	16.59	15.38	8.61	14.24	11.38	12.56	11.51	2.72	12.02	8.91
$[1, \pi_{t-j}, \pi_t^e]$	11.80	6.79	6.70	6.16	**16.47**	12.29	**19.11**	14.93	11.94	**16.27**	**16.75**	**14.93**	11.84	2.96	13.47	14.98
y_{t-1}	9.06	14.98	14.14	9.59	10.76	11.01	6.90	7.92	9.44	10.17	9.91	9.08	8.55	19.51	11.61	12.54
π_{t-2}^m	7.79	9.16	11.80	16.44	6.91	10.07	4.57	5.09	10.65	2.78	3.37	7.71	6.58	10.12	5.70	6.62
$[y_{t-1}, \pi_{t-2}^m]$	10.69	13.04	15.30	15.07	10.09	12.20	7.55	6.45	12.31	9.21	10.22	11.69	5.59	15.06	11.71	13.41
Z_t	12.01	9.16	10.94	10.27	13.21	12.29	21.53	16.74	15.28	15.52	18.44	19.40	13.16	4.94	16.68	16.17
Panel B: Sources																
y_{t-1}	11.43	11.42	11.68	15.75	**17.00**	**21.93**	13.33	18.67	10.46	14.13	16.65	**24.25**	8.88	5.93	9.12	11.44
π_{t-1}	5.90	5.28	7.99	0.00	5.84	11.18	0.65	10.86	**16.02**	**22.48**	27.82	7.84	4.28	3.70	8.50	4.26
π_{t-2}^m	9.32	10.99	11.06	6.85	16.67	14.51	7.08	5.09	12.31	5.67	9.69	18.91	8.22	4.94	4.46	7.73
EONIA	14.11	16.81	16.16	0.00	16.07	14.25	**21.90**	1.92	11.85	21.95	**29.82**	15.55	0.00	20.00	**22.49**	14.51
π_t^{e5}	4.63	5.39	6.70	19.86	8.17	11.52	2.98	7.35	12.04	0.00	2.21	0.00	15.46	8.40	5.49	4.02
AGE	15.64	**19.07**	7.74	2.74	12.15	7.68	13.51	17.87	13.98	9.42	2.95	1.87	**29.28**	13.83	11.81	17.03
OPEN	10.48	0.54	**19.18**	3.42	11.29	3.33	4.38	**22.85**	9.26	14.56	2.63	17.04	11.18	8.15	20.73	**20.74**
DESI	12.74	12.39	10.82	**28.77**	3.45	4.18	**21.90**	0.00	0.46	6.10	4.32	1.87	0.00	**22.47**	3.52	0.79
t	**15.75**	18.10	8.67	22.60	9.36	11.43	14.26	15.38	13.61	5.67	3.90	12.69	22.70	12.59	13.89	19.48

Notes: Values in brackets correspond to the country-specific rejection rates displayed in Figure 3.2. The symbol π_{t-j} is shorthand notation for $[\pi_{t-1}, \dots, \pi_{t-p^*}]'$. Bold (underlined) values in Panel A correspond to those channels other than the unspecified channel Z_t that explain the largest (smallest) amount of rejection rates for the corresponding country. The intercept and $Z_{t,\text{NL}} = \pi_t^e$ are equally important for Slovakia. Bold (underlined) values in Panel B correspond to those sources that explain the largest (smallest) amount of rejection rates for the corresponding country. The EONIA rate and DESI are equally important for Germany. All test for Cyprus with the EONIA rate or lagged inflation as the potential source of nonlinearities fail to reject the null hypothesis. Similarly, all test for the Netherlands with the EONIA rate and DESI as the potential source of nonlinearities fail to reject the null hypothesis.

(being highly correlated with time) and the level of digitalisation seem to induce changes in the intercept of the euro area Phillips curve.[33] In contrast, although prominently discussed in many related studies, a nonlinear effect of slack on inflation driven by the level of slack itself seems to be of secondary importance only. Moreover, long-run inflation expectations, aggregated over all channels the most unimportant source for the euro area according to Table 3.1, is also relatively unimportant considering each channel separately.

3.3 Differences Across Slack and Imported Inflation Measures

To address the measurement issues of slack and imported inflation, all results analyzed so far are aggregated over seven different measures of slack and six different measures of imported inflation. This section briefly assess the impact of different measures of slack

[33] One way to account for variations in the intercept driven by a variable not originally included in (2.1) is to simply add the variable as an additional linear regressor.

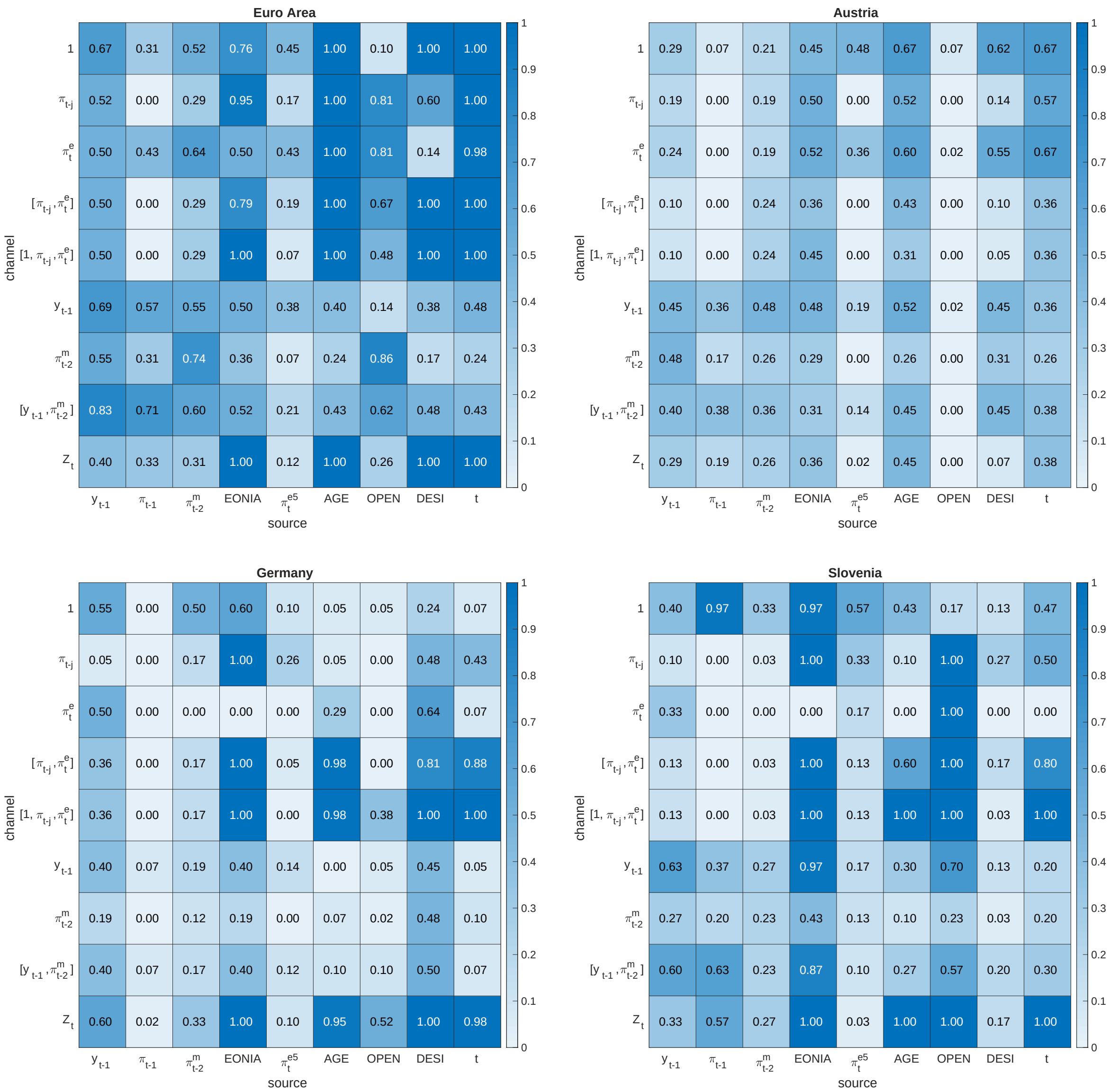

Figure 3.3: Rejection rates for the euro area, Austria, Germany and Slovenia and all combinations of channels and sources. Notes: The symbol π_{t-j} is shorthand notation for $[\pi_{t-1}, \ldots, \pi_{t-p^*}]'$. The color of the cells depends on the magnitude of the rejection rates, with darker shades corresponding to larger rejection rates.

and imported inflation on the results.

To this end, we first decompose the overall rejection rate for the slack channel into the rejection rates obtained for the slack channel conditional upon a specific slack measure and perform analogous calculations for the imported inflation measures. The column labeled "Channel" in Table 3.2 reports the results. As already indicated by the horizontal line in Figure 3.1, the overall rejection rate for the slack channel is equal to 32%, which corresponds to the weighted average in Table 3.2. Considering only those Phillips curve specifications where slack is measured by capacity utilization increases the rejection rate for the slack channel to 38%, whereas choosing the unemployment gap as a measure of slack reduces the rejection rate for the slack channel to 27%. The rejection rates corresponding to the other slack measures lay between these two values. Thus, the choice of the slack measures has a relatively small effect on the rejection rate for the slack channel. In contrast, the choice of the imported inflation measure appears to have a considerably larger effect on the rejection rate for the imported inflation channel. The overall rejection rate for this channel is given by 22%, compare also the horizontal line in Figure 3.1. However, considering only those Phillips curve specifications where imported inflation is measured by foreign demand increases the rejection rate for the imported inflation channel considerably to 36%, whereas choosing the oil price as an imported inflation measures reduces the rejection rate for the imported inflation channel to merely 11%. Thus, the choice of the imported inflation measure appears to have a large effect on the rejection rate for the imported inflation channel.

Next, we decompose the overall rejection rate for slack as the source into the rejection rates obtained for slack as the source conditional upon a specific slack measure and again perform analogous calculations for the imported inflation measures. The column labeled "Source" in Table 3.2 reports the results. The overall rejection rate for slack as a source is equal to 41%, which corresponds to the weighted average in Table 3.2, compare also the discussion in Section 3.1. Considering only those Phillips curve specifications where slack is measured by total employment increases the rejection rate for slack as a source to 53%, whereas choosing the unemployment rate as a measure of slack reduces the rejection rate to 33%. Thus, the choice of the slack measures has a relatively large effect on the rejection rate for slack as a source. In contrast, the rejection rates for imported inflation as a source conditional upon the different imported inflation measures are homogeneous (between 24% and 29%), but foreign demand forms one exception (55%).

We conclude that the choice of the slack measure has only a small effect on the rejection rate for the slack channel, but some measures of slack might be more suitable to capture nonlinearities of the Phillips curve than others. The picture is reversed for imported inflation with the exception of foreign demand. For estimating linear NKPCs it is advantageous to choose slack and imported inflation measures that yield small rejection rates for the slack and imported inflation channel, respectively. On the other hand, when considering nonlinear NKPC specifications it appears to be advantageous to use slack and imported inflation measures as sources that lead to large rejection rates in our analysis. Note, however, that the results in Table 3.2 are aggregated numbers. The effects of different slack and imported inflation measures might be heterogeneous across countries.

Table 3.2: Rejection rates conditional upon slack and imported inflation measures

	Rejection rate	
Measure	Channel	Source
Panel A: slack (y_{t-1})		
Real GDP	0.31	0.41
Unemployment Rate	0.30	<u>0.33</u>
Output Gap	0.32	0.48
Unemployment Gap	<u>0.27</u>	0.41
Capacity Utilization	**0.38**	0.34
Real Investment	0.28	0.39
Total Employment	0.36	**0.53**
Weighted Average	0.32	0.41
Panel B: imported inflation (π^{m}_{t-2})		
Exchange Rate	0.27	0.25
Oil Price	<u>0.11</u>	0.24
Foreign Demand	**0.36**	**0.55**
Import Prices	0.22	0.25
Non-Energy Commodity Prices	0.17	<u>0.24</u>
DG-AGRI	0.21	0.29
Weighted Average	0.22	0.30

Notes: Panel A displays the rejection rates for the slack channel (second column) and for slack as the source (third column) conditional upon the choice of the slack measure. The weighted average in the second column corresponds to the overall rejection rate for the slack channel (already known as the horizontal line in Figure 3.1). The weighted average in the third column corresponds to the overall rejection rate for slack as a source (already discussed in Section 3.1). Bold (underlined) values in each column indicate largest (smallest) rejection rates conditional upon the choice of the slack measure. Panel B contains analogous results for the different imported inflation measures.

4 Summary and Conclusions

Testing the null hypothesis of correct specification of the standard open-economy hybrid NKPC against the alternative of misspecification using auxiliary regressions, this paper presents evidence for nonlinearities and instabilities of the Phillips curve for the euro area and all 15 considered member states. The most important channels of nonlinearities in the NKPC appear to be the intercept and the long-run inflation mean. Aggregated over the euro area and its member states, the main sources of nonlinearities are the EONIA rate, slack and the deterministic time trend. The aggregated results often confirm the importance of specific combinations of channels and sources prominently discussed in the literature, e. g., time-varying intercepts and effects of slack on inflation being dependent on the level of slack (and lagged inflation). In addition, the results also indicate potentially important mechanisms seemingly less discussed in the literature, e. g., effects of the EONIA rate on the long-run inflation mean, or on the effect of slack on inflation. However, evidence for nonlinearities and instabilities and importance of specific combinations of channels and sources vary across countries. Nevertheless, it appears that understanding the impacts of long-term structural factors like demographic trends on inflation better is at least as important as obtaining a better understanding of a nonlinear impact of cyclical drivers like slack on inflation. Interestingly, we detect for the euro area and several member states some combinations of channels and sources which lead to a rejection of the null hypothesis of correct specification for all slack and imported inflation measures. These combinations may be of particular interest when considering nonlinear NKPC specifications in future research.

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References

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control* **19**, 716 – 723.

Angelini, E., Bokan, N., Christoffel, K., Ciccarelli, M. and Zimic, S. (2019). Introducing ECB-BASE: The blueprint of the new ECB semi-structural model for the euro area. Working Paper 2315, European Central Bank.

Bacon, D.W. and Watts, D.G. (1971). Estimating the transition between two intersecting straight lines. *Biometrika* **78**, 525–534.

Bańbura, M. and Bobeica, E. (2020). Does the Phillips curve help to forecast euro area inflation? Working Paper 2471, European Central Bank.

Barnes, M.L. and Olivei, G.P. (2003). Inside and outside bounds: Threshold estimates of the Phillips curve. *New England Economic Review* **2003**, 3–18.

Bobeica, E. and Jarociński, M. (2017). Missing disinflation and missing inflation: The puzzles that aren't. Working Paper 2000, European Central Bank.

Bobeica, E., Lis, E., Nickel, C. and Sun, Y. (2017). Demographics and inflation. Working Paper 2006, European Central Bank.

Brand, C., Bielecki, M. and Penalver, A. (2018). The natural rate of interest: Estimates, drivers, and challenges to monetary policy. Occasional Working Paper 217, European Central Bank.

Ciccarelli, M. and Osbat, C. (2017). Low inflation in the euro area: Causes and consequences. Occasional Paper 181, European Central Bank.

Colavecchio, R. and Ruebene, I. (2020). Non-linear exchange rate pass-through to euro area inflation: A local projection approach. Working Paper 2362, European Central Bank.

Cogley, T. and Sbordone, A. (2008). Trend inflation, indexation, and persistence in the new Keynesian Phillips curve. *American Economic Review* **98**, 2101–2126.

Costain, J., Nakov, A. and Petit, B. (2019). Monetary policy implications of state-dependent prices and wages. Working Paper 1910, Bank of Spain.

Daly, M.C. and Hobijn, B. (2014). Downward nominal wage rigidities bend the Phillips curve. *Journal of Money, Credit and Banking* **46**, 51–93.

Davies, R.B. (1977). Hypothesis testing when a nuisance parameter is present only under the alternative. *Biometrika* **64**, 247–254.

Davies, R.B. (1987). Hypothesis testing when a nuisance parameter is present only under the alternative. *Biometrika* **74**, 33–44.

Eser, F., Karadi, P., Lane, P.R., Moretti, L. and Osbat, C. (2020). The Phillips curve at the ECB. *The Manchester School* **88**, 50–85.

Eurostat(a). https://ec.europa.eu/eurostat/statistics-explained/index.php?title=File:Median_age_of_population,_2011_and_2021_(years)_rev.png (accessed: March 21, 2022)

Eurostat(b). https://ec.europa.eu/eurostat/statistics-explained/index.php?title=File:Increase_in_the_share_of_the_population_aged_65_years_or_over_between_2011_and_2021_(percentage_points)_rev.png (accessed: March 21, 2022)

Forbes, K. (2020). Inflation dynamics: Dead, dormant, or determined abroad? *Brookings Papers on Economic Activity, Fall 2019 Meetings*, 257–319.

Forbes, K., Gagnon, J. and Collins, C.G. (2021). Low inflation bends the Phillips curve around the world. Working Paper 29323, National Bureau of Economic Research.

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

Giannone, D., Lenza, M., Momferatou, D. and Onorante, L. (2014). Short-term inflation projections: A Bayesian vector-autoregressive approach. *International Journal of Forecasting* **30**, 635–644.

Goldfeld, S.M. and Quandt, R.E. (1972). *Nonlinear Methods in Econometrics*. North-Holland, Amsterdam.

Goldfeld, S.M. and Quandt, R.E. (1973). A Markov model for switching regressions. *Journal of Econometrics* **1**, 3–15.

Gross, M. and Semmler, W. (2019). Mind the output gap: The disconnect of growth and inflation during recessions and convex Phillips curves in the euro area. *Oxford Bulletin of Economics and Statistics* **81**, 817–848.

Hamilton, J.D. (1989). A new approach to the analysis of nonstationary time series and the business cycle. *Econometrica* **57**, 357–384.

Hamilton, J.D. (1990). Analysis of time series subject to changes in regime. *Journal of Econometrics* **45**, 39–70.

Hansen, B.E. (1995). Rethinking the univariate approach to unit root testing. *Econometric Theory* **11**, 1148–1171.

Hansen, B.E. (2000). Sample splitting and threshold estimation. *Econometrica* **68**, 575–603.

Kamber, G., Mohanty, M., Morley, J. (2020). Have the Driving Forces of Inflation Changed in Advanced and Emerging Market Economies? BIS Working Papers 896.

Kanellopoulos, N.C. and Koutrolis, A.G. (2016). Non-linearities in euro area inflation persistence. *Economic Modelling* **59**, 116–123.

Kim, C.-J., Piger, J. and Startz, R. (2008). Estimation of Markov regime-switching regression models with endogenous switching. *Journal of Econometrics* **143**, 263–273.

Koester, G., Lis, E., Nickel, C., Osbat, C., Smets, F. (2021). Understanding Low Inflation in the Euro Area From 2013 to 2019: Cyclical and Structural Drivers. Occasional Working Paper 280, European Central Bank.

Jarociński, M. and Karadi, P. (2020). Deconstructing monetary policy surprises – the role of information shocks. *American Economic Journal: Macroeconomics*, **12**, 1–43.

Juselius, M. and Takáts, E. (2019). The age-structure–inflation puzzle. Research Discussion Papers 4/2016, Bank of Finland.

Lagarde, C. (2020). The monetary policy strategy review: Some preliminary considerations. *Speech*, ECB and Its Watchers XXI.

Lis, E., Nickel, C. and Papetti, A. (2020). Demographics and inflation in the euro area: A two-sector new Keynesian perspective. Working Paper 2382, European Central Bank.

Luukkonen, R. Saikkonen, P. and Teräsvirta, T. (1988). Testing linearity against smooth transition autoregressive models. *Biometrika* **75**, 491–499.

Macklem, T. (1997). Capacity constraints, price adjustment, and monetary policy. *Bank of Canada Review* **1997**, 39–56.

Mavroeidis, S., Plagborg-Mòller, M. and Stock, J.H. (2014). Empirical evidence on inflation expectations in the new Keynesian Phillips curve. *Journal of Economic Literature* **52**, 124–188.

Oinonen, S. and Paloviita, M. (2014). Updating the euro area Phillips curve: The slope has increased. Discussion Paper 31/2014, Bank of Finland.

Perron, P. (1989). The great crash, the oil price shock, and the unit root hypothesis. *Econometrica* **57**, 1361–1401.

Ramsey, J.B. (1969). Tests for specification errors in classical linear least-squares regression analysis. *Journal of the Royal Statistical Society. Series B 31*, 350–371.

Rostagno, M. Altavilla, C., Carboni, G., Lemke, W., Motto, R., Saint Guilhem, A. and Yiangou, J. (2021). Monetary Policy in Times of Crisis: A Tale of Two Decades of the European Central Bank. Oxford University Press, Oxford.

Schwarz, G. (1978). Estimating the dimension of a model. *Annals of Statistics* **6**, 461–464.

Smets, F. (2010). Commentary: Modeling inflation after the crisis. In *FRB Kansas city symposium, Jackson Hole, Wyoming, August 26–28, 2010.*

Szörfi, B. and Tóth, M. (2018). Measures of slack in the euro area. ECB Economic Bulletin Box, Issue 3/2018.

Teräsvirta, T. (2004). Smooth transition regression modeling. In: Lütkepohl, H. and Krätzig, M. (Eds.) *Applied Time Series Econometrics.* Cambridge University Press, Cambridge, 222–242.

Teräsvirta, T., Tjøstheim, D. and Granger, C.W.J. (2010). *Modelling Nonlinear Economic Time Series.* Oxford University Press, Oxford.

Weidmann, J. (2018). Higher growth, lower inflation? – Digitalisation from a central bank's perspective. *Speech*, Annual meeting of the German Economic Association.

Appendices

A Data

Table A.1: Variables

Symbol	Variable name	Original variable (OV)	Source	Transformation of OV before entering the analysis
π_t	Inflation	Harmonized index of consumer prices, seasonally adjusted	ECB LIFT	y-o-y growth rate
π_t^{e}	Inflation expectations (short-term)	Price trends over next 12 months, seasonally adjusted balances*	ECB LIFT, European Commission	
π_t^{e5}	Inflation expectations (long-term)***	Expected rates of inflation (point forecasts) for a 5y horizon	ECB LIFT, ECB Survey of Professional Forecasters	
y_t	Real GDP	Gross domestic product at market prices, seasonally adjusted	ECB LIFT, Eurostat	y-o-y growth rate
	Unemployment rate	Harmonized unemployment rate (in % of labor force), seasonally adjusted	ECB LIFT, Eurostat Labor Force Survey	multiplied by -1
	Output gap**	Percentage deviation of the actual level of real GDP from the potential level	ECB LIFT, MPD	
	Unemployment gap**	Difference between the unemployment rate and the non-accelerating inflation rate of unemployment	ECB LIFT, MPD	multiplied by -1
	Capacity utilization	Capacity utilization in manufacturing (percentage of total production capacity)	ECB LIFT, European Commission DG-ECFIN business survey	divided by 100
	Real investment	Gross fixed capital formation (in mil. EUR), seasonally adjusted	ECB LIFT, Eurostat	y-o-y growth rate
	Total employment	Total domestic employment (in thousands of persons)	ECB LIFT	y-o-y growth rate
π_t^{m}	OIL***	Oil price (in USD)	ECB LIFT	y-o-y growth rate
	Import prices	Import deflator (goods and services)	ECB LIFT, Eurostat	y-o-y growth rate
	Non-energy commodity prices**	Non-energy commodity prices (in USD), seasonally adjusted	ECB LIFT, MPD	y-o-y growth rate
	Exchange rate***	EUR/USD	ECB LIFT	multiplied by -1
	Foreign demand**	Weighted geometric average of imports of extra-euro area trading partners	ECB LIFT, MPD	y-o-y growth rate
	DG-AGRI**	Euro area farm gate prices based on European Commission data	ECB LIFT, MPD	y-o-y growth rate
	AGE	Share of population aged 65 years and more	Eurostat, authors' calculations	
	DESI	Share of individuals performing an online purchase in last 3 months	Eurostat, authors' calculations	y-o-y growth rate
	OPEN	Exports plus imports as a share of GDP	Eurostat, authors' calculations	y-o-y growth rate
	EONIA***	3-month EONIA rate	ECB	

Notes: LIFT and MPD refer to the Low Inflation Task Force and the Macroeconomic Projection Database of the European Central Bank (ECB). AGE and DESI were converted from annual frequency to quarterly frequency using the linear conversion method and the quadratic average method, respectively. Since 1 January 2022, the EONIA rate is replaced by the euro short-term rate (€STR). In the transition period between 2 October 2019 and 31 December 2021, the EONIA rate was defined as €STR plus 8.5 basis points. *Balances are calculated as the difference between the percentages of respondents giving positive and negative replies; **Confidential variables; ***Common variables across countries.

Table A.2: Country-specific sample periods and missing variables

Country	ISO code	Sample period	Missing variables
Euro Area	EA	2003Q1 – 2020Q1	
Austria	AT	2003Q1 – 2020Q1	
Belgium	BE	2006Q1 – 2020Q1	
Cyprus	CY	2005Q1 – 2017Q2	Output gap, Unemployment gap, Import prices
Estonia	EE	Missing	
Finland	FI	2003Q1 – 2020Q1	
France	FR	2007Q1 – 2020Q1	
Germany	DE	2003Q1 – 2020Q1	
Greece	GR	2003Q1 – 2020Q1	
Ireland	IE	Missing	
Italy	IT	2006Q1 – 2020Q1	
Latvia	LV	2005Q1 – 2020Q1	
Lithuania	LT	2005Q1 – 2020Q1	
Luxembourg	LU	2003Q1 – 2020Q1	
Malta	MT	Missing	
Netherlands	NL	2003Q1 – 2019Q4	Import prices, Non-energy commodity prices, Foreign demand
Portugal	PT	Missing	
Slovakia	SK	2005Q1 – 2017Q4	Output gap, Unemployment gap, Foreign demand
Slovenia	SI	2005Q1 – 2020Q1	Unemployment gap, Foreign demand
Spain	ES	2003Q1 – 2020Q1	

Notes: Import prices for Slovenia are calculated on the basis of real and nominal import prices from the Bank of Slovenia internal database. Non-energy commodity prices is proxied by series calculated under the assumption that oil prices contribute ten percent to the import prices, while the rest of the contribution stems from non-energy commodity prices.

B Supplementary Material: Additional Empirical Results

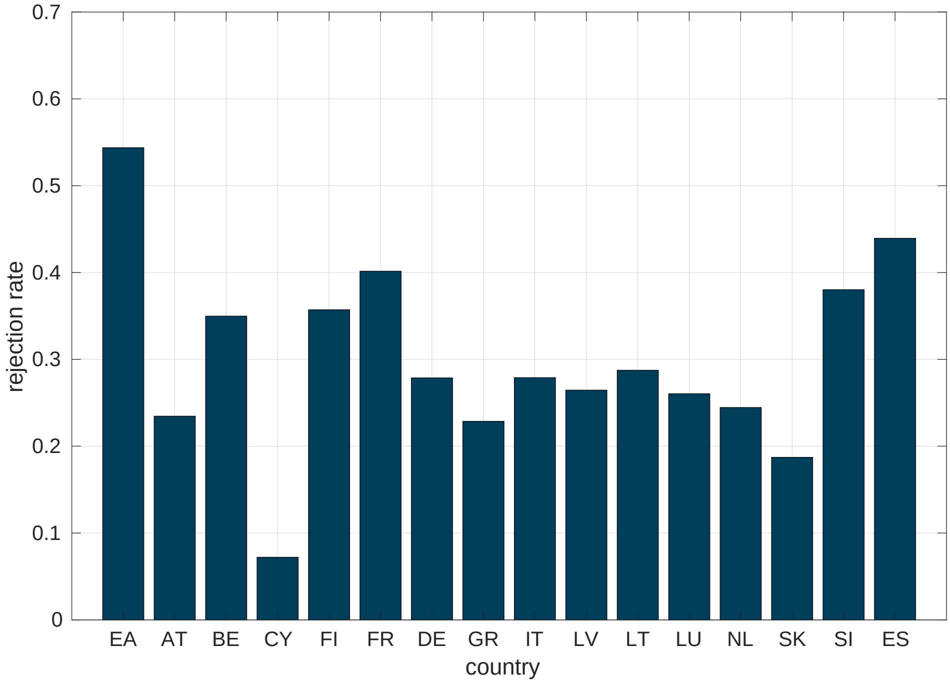

Figure B.1: Country-specific rejection rates in case all samples end in 2017Q2

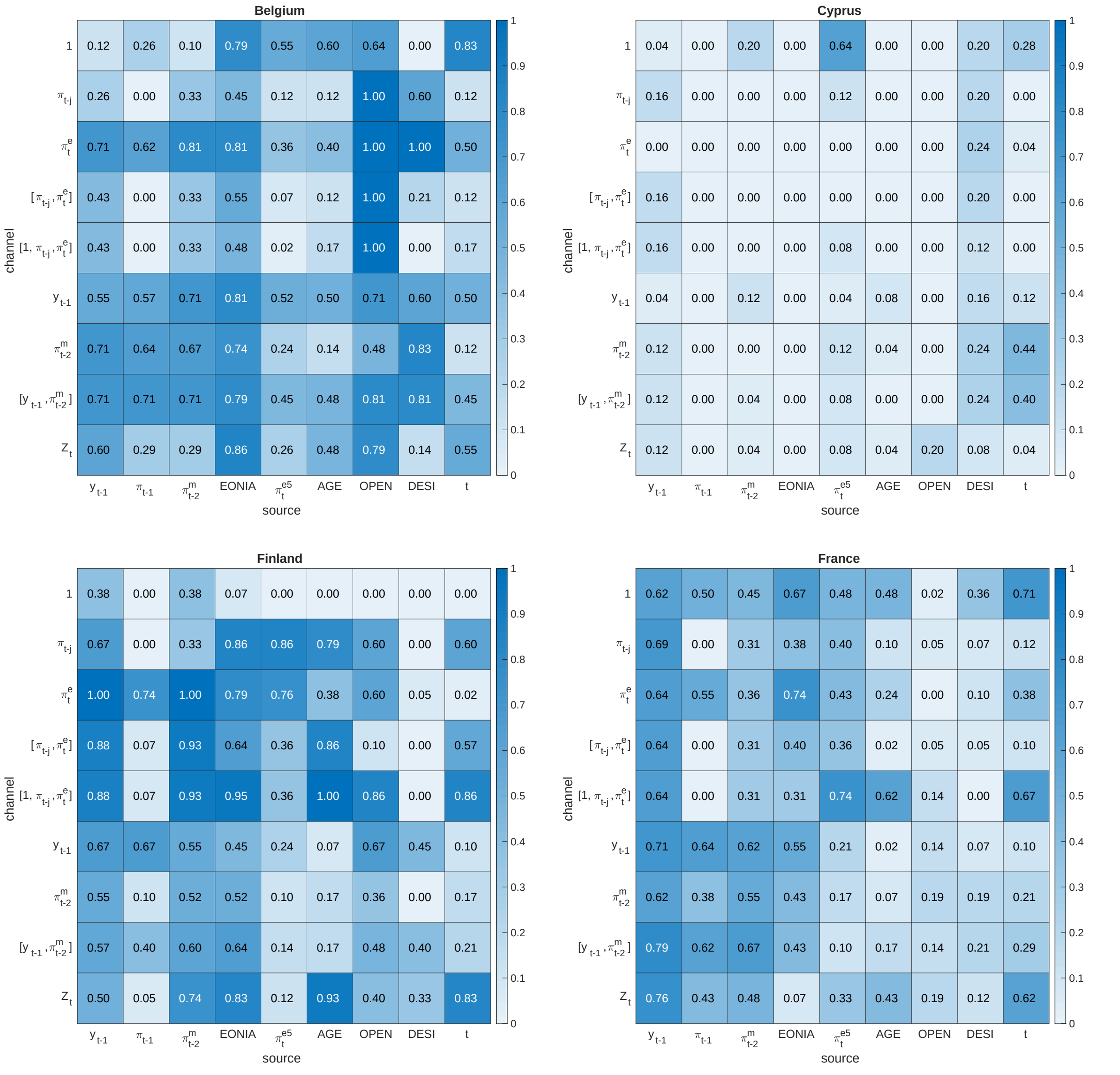

Figure B.2: Rejection rates for Belgium, Cyprus, Finland and France and all combinations of channels and sources. Notes: See notes to Figure 3.3.

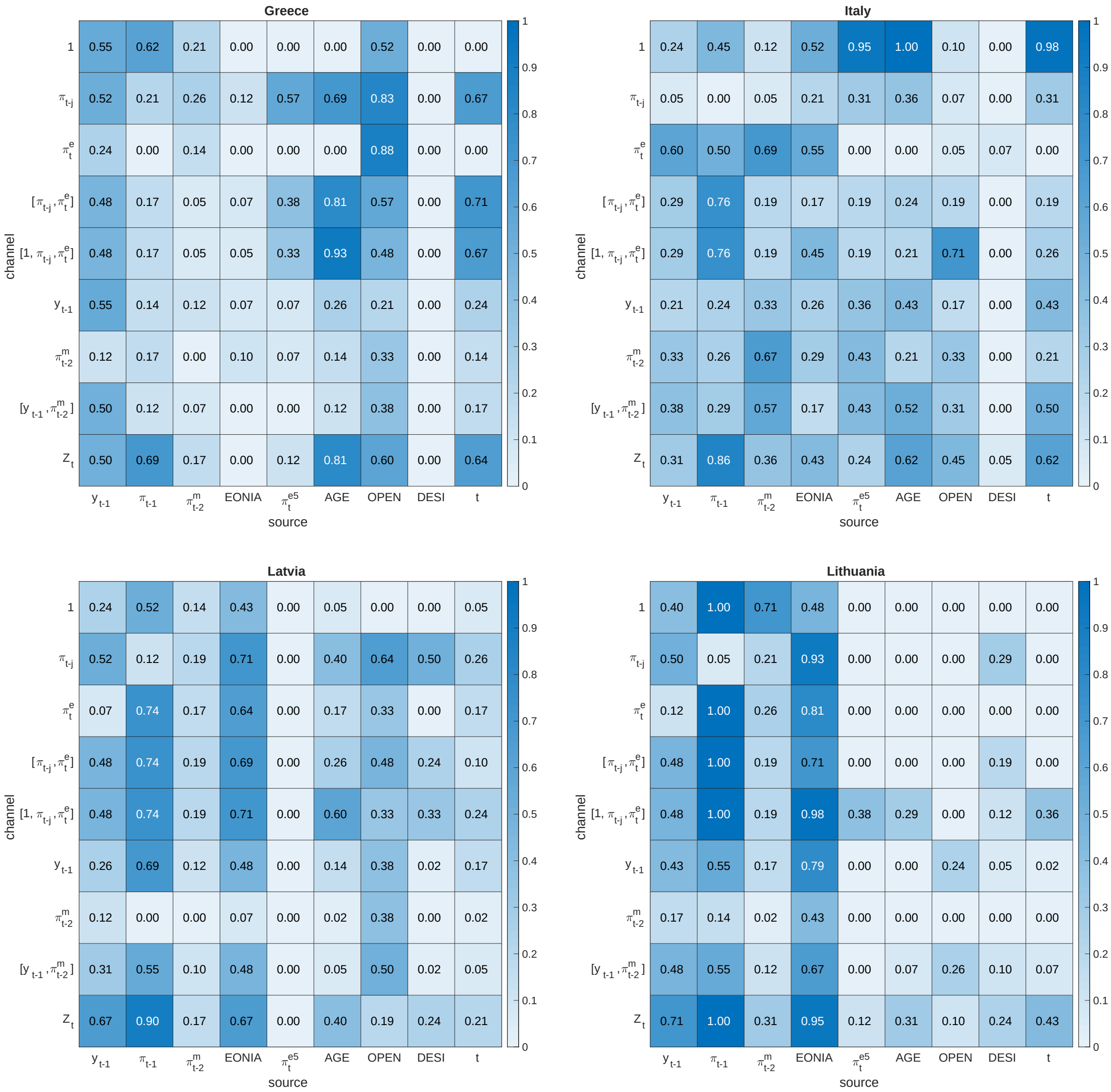

Figure B.3: Rejection rates for Greece, Italy, Latvia and Lithuania and all combinations of channels and sources. Notes: See notes to Figure 3.3.

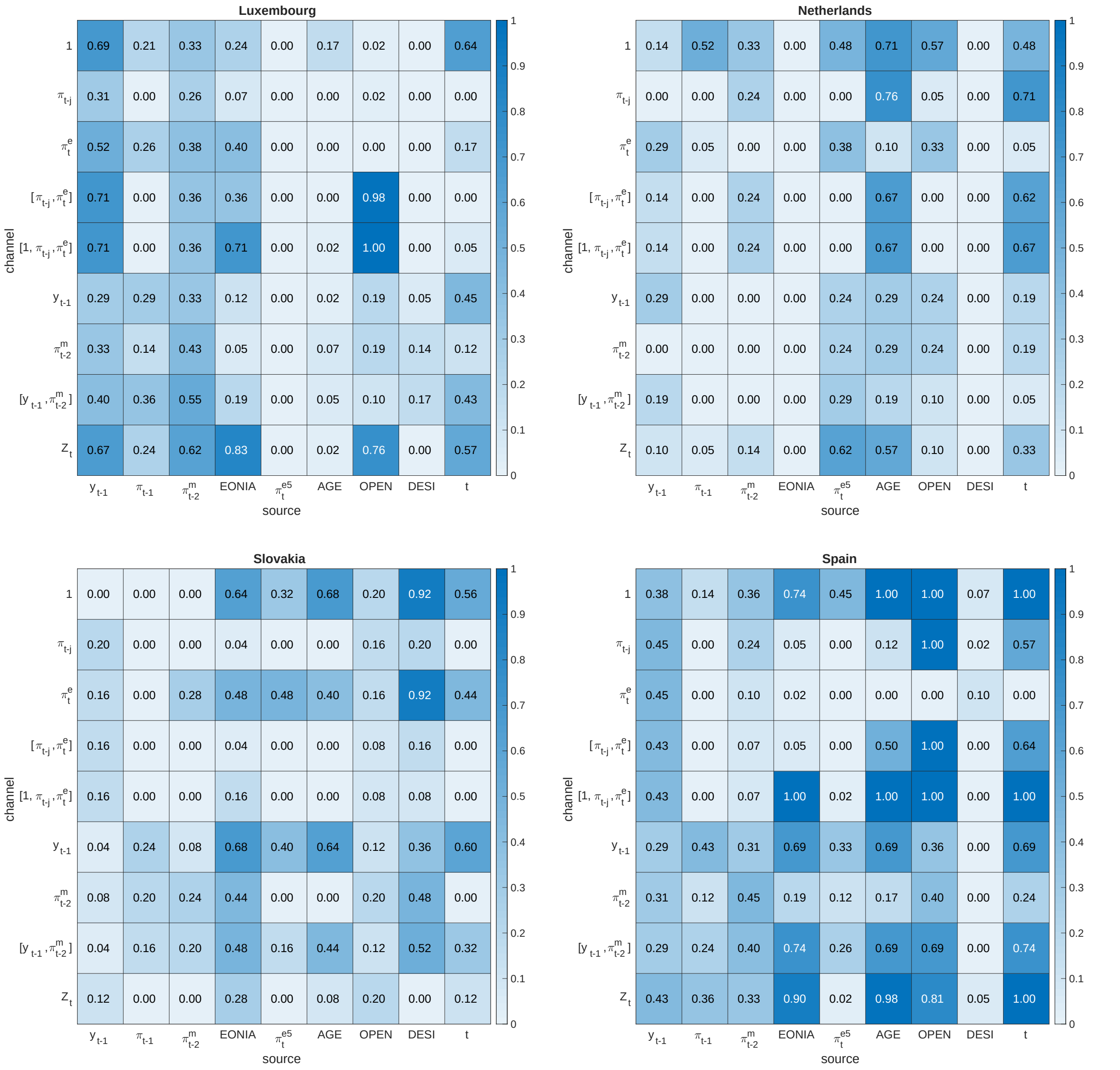

Figure B.4: Rejection rates for Luxembourg, the Netherlands, Slovakia and Spain and all combinations of channels and sources. Notes: See notes to Figure 3.3.