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LOAN SUPPLY SHOCKS, PRUDENTIAL REGULATION, AND THE BUSINESS CYCLE *

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Abstract

How do the business cycle effects of loan supply shocks depend on the state of prudential regulation in the euro area? To address this question, we first identify regulatory cycles from a cumulative prudential policy index that tracks the evolution of the regulatory stance in the euro area. Using sign restrictions in a local projections framework with state-dependency, we identify loan supply shocks and analyse their business cycle effects in regimes with tight and loose prudential regulation. We find that in tight regimes, expansionary shocks trigger a boom-bust cycle. In the loose regime, results appear inconclusive. We also see quite some tendencies toward asymmetry in the responses across regimes. To some extent, however, the results depend strongly on the cycle identified. While our results for the tight regime are very robust across different specifications, the effect of shocks on the business cycle is sensitive to identified loose regimes. The main reason is the historical development of prudential regulation in the euro area, which is primarily characterized by prudential tightening.

The views expressed in this paper are those of the author and do not necessarily represent those of the Deutsche Bundesbank or the Eurosystem.

Keywords: Prudential Regulation, Business Cycle, Loan Supply, Euro Area, State Dependence, Local Projections, Sign Restrictions.
JEL classification: C54, E32, E50, G28

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1 Introduction

Loan supply shocks unfold significant business cycle effects in the euro area, as documented by Barauskaitė et al. (2022), Mandler and Scharnagl (2020), Altavilla et al. (2019), Gilchrist and Mojon (2018), and Gambetti and Musso (2017), among others.

However, the economic effects of loan supply shocks can turn into a pernicious dynamic if they forge a path of excessive credit growth. The latter poses a serious threat to growth and financial stability, as shown in e.g. Sufi and Taylor (2022), Mian et al. (2017), Jordà et al. (2016), Jordà et al. (2013), Schularick and Taylor (2012).

Prudential regulation has proven its usefulness in tackling these trends and strengthening the resilience of the financial system. For example, (macro-)prudential instruments can help reduce credit growth (i.a. Kim and Mehrotra, 2022, Jiménez et al., 2017, Akinci and Olmstead-Rumsey, 2018, Cerutti et al., 2017, and Fendoğlu, 2017), house price inflation (e.g. Kuttner and Shim, 2016 or Duca et al., 2021 and the extensive literature therein), or curb the credit cycle (i.a. Jiménez et al., 2017 or Fendoğlu, 2017).[1]

But how does prudential regulation interplay with the business cycle effects of loan supply shocks? Does the regulatory regime determine the economic effects of said disturbances? This paper addresses these questions. To this end, we apply state-dependent local projections which allow the identification of loan supply shocks by means of sign restrictions and analyse their effects on economic activity. In order to examine the role of prudential regulation, we consider different regulatory regimes.

Moreover, this approach allows us to investigate whether there are asymmetric effects with regard to regulatory regimes, as there are a number of factors that could explain possible asymmetry in the propagation of loan supply shocks across the state of prudential regulation.

First, as noted by De Schryder and Opitz (2021), it may be that tightening measures are design generally more restrictive than loosening measures are easing.[2]

[1] Also the unsystematic elements of (macro-)prudential regulation can help combat undesirable developments by influencing credit growth (Budnik and Rünstler, 2023, Kim and Mehrotra, 2022, De Schryder and Opitz, 2021, Richter et al., 2019), house price inflation (Budnik and Rünstler, 2023, Bachmann and Rüth, 2020, Richter et al., 2019) or promoting financial stability (Fernandez-Gallardo, 2023, Hristov et al., 2021).

[2] Poghosyan (2020) finds asymmetric effects of loosening and tightening measures, with the former having a stronger effect on credit developments. Even though his approach also uses the MaPPED, the results are

Second, even if tight and loose measures are designed and used symmetrically, the timing and thus the existing regulatory environment at which they are implemented can lead to asymmetries if the marginal effects of prudential measures themselves are non-linear. Assume that the regulatory authority implements a tight measure at time t in the face of expansionary credit developments.[3] Irrespective of whether the general regulatory stance is loose or tight at that time, it will be relatively more restrictive in $t + 1$. However, if there are non-linear marginal effects of prudential policy measures, the additional tightening will have bigger consequences in an already tight regime than the same measure if it is introduced in a loose regime.

The banks' lending behaviour is another potential source of asymmetry. Rodano et al. (2018) examine how lending to small and medium enterprises (SME) changes over the credit cycle and, in particular, the role played by the credit ranking of the enterprises in Italy. The authors do not find any indications of a different allocation of loans to performing SME (i.e. SME with a good credit ranking) as against enterprises that are ranked sub-standard by banks in phases of a credit expansion. More specifically, both groups receive roughly the same amount of loans volumes. Credit terms also differ only marginally, as the interest rate differential for loans to sub-standard SME is only 20 basis points above the interest performing SME have to pay on their loans. However, this equal treatment changes in bust periods as banks' funding costs for wholesale funds deteriorate, thus rationing loans and excluding sub-standard SME. This adjusted allocation behaviour has real effects. In crises, the output of performing SME is just over 50% above the output of SME rated sub-standard. This is primarily due to the fact that performing SME can invest more in crises, as they are still able to get loans. Furthermore, downgrades of enterprises in the bust

not necessarily transferable to ours for several reasons. Poghosyan (2020) uses a sample consisting of 28 EU countries, while focusing only on the role of lending restrictions in his analyzes. As a result of this limitation, only five euro area countries with loosening measures and nine euro area member states with tightening measures are represented in his sample. This means that part of the asymmetry may have been caused by country group-specific effects. This is also indicated by the fact that he finds contradictory effects of lending restrictions if he distinguishes between euro area countries and other EU member countries. For the latter, restrictions have the expected effect, while restrictive measures in euro area countries lead to an increase in loans. The author himself also points out that the contradictory results should be taken with a grain of salt and explains the results in particular with the incapability of the euro area member states to conduct individual monetary and exchange rate policies. We circumvent this problem by looking at the euro area as a whole.

[3] Kim and Mehrotra (2022) show in their panel analysis considering 32 advanced economies, that expansionary shocks to credit are in general met with macroprudential tightening measures. Boar et al. (2017) also report a strong response of macro-prudential policy to credit and output growth for 64 advanced and emerging economies.

phase can also lead to a self-reinforcing downward spiral, as downgraded SME receive 39% less loans than SME, that have not been downgraded. This asymmetric lending behaviour can be triggered or may be further exacerbated by regulatory restrictions imposed on banks.

We find that loan supply shocks lead to boom-bust-phases. In the first year after the shock materialises, there is an expanding business cycle. This effect is reversed in the following years. So far, this is nothing new. What is new, however, is that the boom-bust-cycle is more pronounced in a tighter regulatory regime than in a comparatively looser regime. What's more, the bust-phase lasts longer in the loose regime. We observe that credit growth can follow a sustained positive growth path as a result of an expansionary loan supply shock. However, this effect is largely dependent on the underlying regulatory cycle, which distinguishes between loose and tight phases.

Furthermore, we do not find any clear patterns of asymmetry in the responses to the shocks across regimes. This is also due to the fact that the impulse responses vary considerably depending on how the regulatory regime is identified. This is because loose regimes are more difficult to identify, as prudential regulation has followed a clear trajectory of tightening in the past. Consequently, the results for the tight regime turn out to be extremely robust.

The remainder of this paper is as follows. In section 2, we calculate the cumulative prudential policy index, which quantifies the development of the regulatory stance in the euro area. The econometric model is described in section 3. Section 4 is dedicated to the determination of regulatory regimes. In section 5, we analyse the role of regulatory regimes on the effects of loan supply shocks on the business cycle and assess possible asymmetric effects. We run a number of robustness checks section 6 before section 7 concludes.

2 Prudential Policy in the Euro Area

We derive the evolution of prudential policy in the euro area from the Macroprudential Policy Evaluation Database.[4] It is the outcome of a standardized questionnaire that was completed by the national central banks and supervisory authorities and contains information about prudential policy actions taken in the European Union. Information

[4]As the detailed description of the MaPPED is out of scope of this paper, we refer the interested reader to Budnik and Kleibl (2018).

concerning the character of a policy were categorized by the respondents as either i) *Macroprudential*, ii) *Macroprudential, Microprudential* or iii) *Macroprudential, Microprudential, Other*. For our analysis, we incorporate all responses from all three categories given by Eurozone member countries. This gives us a total of 370 prudential measures.[5]

In order to translate the 370 reported measures into an index that captures the stance of prudential policy in the euro area, we adopt the approach of Akinci and Olmstead-Rumsey (2018), among others, and proceed as follows.[6]

First, we code every reported measure into a balanced ternary on a country-quarter basis. The information on the effect of a measure stem from the MaPPED questionnaire, as the respondents were asked to indicate whether the reported policy was (intended as) a *policy tightening*, *policy loosening*, or something *other and with ambiguous impact*.[7] Consequently, measure m of category k in country i at time t is coded as $+1$ (-1) if it is a policy tightening (loosening). Measures with an ambiguous effect are coded as zero, i.e.

$$m^k_{i,t} = \begin{cases} +1, \text{ if} & \textit{tightening} \\ -1, \text{ if} & \textit{loosening} \\ 0, \text{ if} & \textit{ambiguous}\,. \end{cases} \tag{2.1}$$

In the MaPPED, some measures are accompanied by information concerning their announcement period. In that cases, t refers to the announcement period. In all other cases, t relates to the period the measures came into force.

The inevitable flaw of this procedure, with which the existing literature has also to cope, is that all measures are weighted equally across both, instruments and time and thus have an identical impact on the index. This is because in most cases, information concerning prudential measures are stated in qualities, rather than quantities.

As a consequence, it is impossible to adequately weight measures not only

[5]The 370 observations break down by category as follows: 316 instances *Macroprudential*, one instance *Macroprudential, Microprudential*, and 53 instances *Macroprudential, Microprudential, Other*.

[6]This approach is also used by Kim and Mehrotra (2022), Hristov et al. (2021), and Cizel et al. (2019), for example.

[7]It should be noted that the response option *other and with ambiguous impact* itself introduces some degree of uncertainty into the index.

within and across instruments, but also across time.[8] In addition, if non-linear effects arise from the use of different measures, they would not be accounted for by the approach here.

Summing the measures across categories $k = 1, ..., K$ results in the *country-specific prudential policy indicator*, which indicates prudential policy changes in country i and quarter t.[9] Formally,

$$PPI_{i,t} = \sum_{k=1}^{K} m_{i,t}^{k} \; . \tag{2.2}$$

Note that with this procedure, tightenings and loosenings which are introduced within the same quarter in a given country ultimately cancel out. Thus, an index of, say two, connotes that there have been *net* two more tightening measures introduced than loosening measures, no matter how many measures have been introduced in total.

In the second step, we weight the country-specific prudential policy indicators by the relative contribution that a member country has made to total GDP of the euro area at a given quarter t in order to get the *GDP-weighted euro area prudential policy indicator*, i.e.

$$PPI_{EA,t} = \sum_{i=1}^{N} \omega_{i,t} PPI_{i,t} \; . \tag{2.3}$$

The constructed indicator shows net changes in the regulatory environment in the euro area.[10]

In the last step, we cumulate the prudential policy indicator across time,

[8] However, there exists literature that quantifies prudential measures, yet incorporates LTVs only. See Richter et al. (2019) or Bachmann and Rüth (2020). Meuleman and Vander Vennet (2020) map the life cycle of a measure with weightings depending on the extent to which the measure is adapted (activation or deactivation of a tool, change in scope or level of an existing tool, maintenance of the existing scope or level of a tool). However, the weights are arbitrary. Also, the different measures are not contrasted with corresponding weights.

[9] Our sample includes a total of $K = 10$ categories reaching from capital-based measures such as capital buffers or risk weights, to borrower-based measures such as caps on LTV or DTI ratios, as well as liquidity-based measures such as asset-based reserve requirements or caps on short- and long-term maturity.

[10] In robustness section 6.2, we use the weighting on the basis of the relative amount of nominal outstanding loans. The biggest obstacle here is that the data is generally only starts from 2003 at the earliest. Reliable figures are thus available for a much shorter observation period. Therefore, we use weights based on GDP as our baseline specification. However, this may lead to changes in the index solely as a result of changes in the relative country weights. In another robustness exercise in section 6.3 we therefore examine whether our results change when we use an unweighted index. As will be seen later, this does not alter our results.

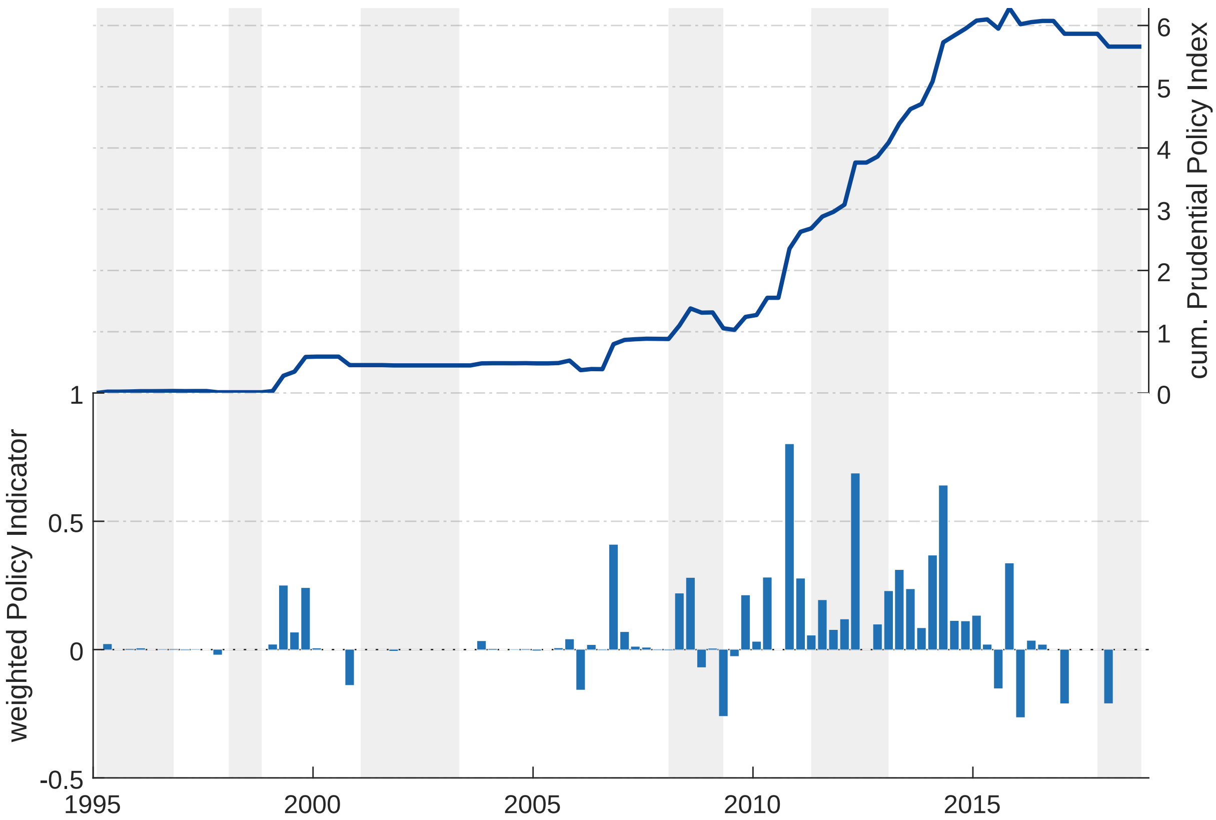
i.e.

$$cPP_t = \sum_{s=0}^{s=t} PPI_{EA,t} \ . \tag{2.4}$$

The resulting *cumulative Prudential Policy-Index* is a proxy for the prudential policy stance and captures prudential effects, which impact can extend far beyond the period in which they were introduced. However, as will be shown in the later part of the paper, we are eventually interested in the trend component of the index, so its level plays a minor role for our purposes.

Figure 1 illustrates the GDP-weighted euro area prudential policy indicator PPI_{EA} (bottom panel) as well as the resulting cumulative Prudential Policy-Index cPP (upper panel). Between 1995 and 2018, prudential policy in the euro area became substantially tight, which can be divided into three phases. Firstly, the prudential policy stance became

Figure 1: GDP-weighted Prudential Policy



Note: Evolution of the policy stance (upper panel) and its quarterly net changes (lower panel). Negative values indicate net loosenings, while positive values show net tightenings. Grey bars mark OECD based recession indicators.

tighter before the millennium. This was partly due to spillover effects of the

Russian and Asian crisis in 1997/1998, which led to prudential tightening. Secondly, in the years before the outbreak of the Great Financial Crisis, prudential policy in the euro area remained on a constant level. Finally, the outburst of the Financial Crisis in 2007, however, ushered in a period of steady tightening, which lasted until the end of 2014. After some loosening measures in mid-2015 and early 2016, the prudential policy stance in the euro area moved at a stable, but historically high level.[11]

3 Econometric Methodology

Local projections (LPs), as proposed by Jordà (2005), are a widely used and highly flexible analysis tool. For example, they are more robust against misspecification at finite lag lengths, since possible errors are not carried along over the entire projection horizon as is the case within VARs, where impulse responses are generated iteratively. In LPs, on the other hand, the reduced-form coefficients are estimated separately. In the end, however, they are merely different projection techniques. Plagborg-Møller and Wolf (2021) show that in an infinite sample with unrestricted lag structure, VARs and LPs estimate identical impulse responses. Thus, they allow identification of structural shocks i.a. by means of sign restrictions. Moreover, they are suitable for analyses of non-linear effects, as used by Tenreyro and Thwaites (2016), Ramey and Zubairy (2018) or Finck and Rudel (2022), or a combination of both, as applied by Alpanda et al. (2021) or Finck et al. (2023).[12]

In general, the idea of local projections is to perform a series of regressions for each horizon, h, and each variable of interest, i, from a set of variables, y_t, on a set of controls. The linear model can be formulated as

$$y_{i,t+h} = \alpha_{i,h} + \boldsymbol{\beta}_{i,h} y_t' + \boldsymbol{\gamma}_{i,h} x_t' + u_{i,h,t} \,, \tag{3.1}$$

where $y_{i,t+h}$ denotes the i-th endogenous variable in the $n \times 1$ vector y_t at time $t+h$. The constants are collected in $\boldsymbol{\alpha}_h$, while $\boldsymbol{\beta}_{i,h}$ and $\boldsymbol{\gamma}_{i,h}$ capture the projection coefficients for the controls in y_t and x_t, respectively. Impulse responses are constructed as a sequence of the coefficients $\boldsymbol{\beta}_{i,h}$ for horizons

[11] For a extensive description of macroprudential policy in Europe, see Budnik and Kleibl (2018).

[12] Methodologically, we follow Finck et al. (2023), who examine the role of a flexible exchange rate for the propagation of negative domestic demand shocks between different monetary regimes. Hence, we mainly rely on their notation in the following.

$h = 0, \ldots, H$. The result is the response of y_i at time $t + h$ to a structural shock that hits the economy at time t. The $n \times p$ vector $\gamma_{i,h} = \left[\phi_{i,h,1}, \ldots, \phi_{n,h,1}, \phi_{i,h,2}, \ldots, \phi_{n,h,2}, \ldots, \delta_{n,h,p}\right]$ collects the coefficients for the covariates in $x_t = \left[y_{t-1}, \ldots, y_{t-p}, 1\right]$, i.e. the p lags of y_t. Finally, the projection residual of the i-th variable at horizon h in t is denoted by $u_{i,h,t}$ and has a (strictly) positive variance.

A. *Specification of State-Dependent Local Projections with Sign Restrictions*

The non-linear, state-dependent extension of the linear model can be written as

$$y_{i,t+h} = (1 - S_t)\left[\alpha_{i,h}^{tight} + \beta_{i,h}^{tight} y_t' + \gamma_{i,h}^{tight} x_t'\right] + S_t\left[\alpha_{i,h}^{loose} + \beta_{i,h}^{loose} y_t' + \gamma_{i,h}^{loose} x_t'\right] + u_{i,h,t}\,, \quad (3.2)$$

where S_t is a state-variable which will be introduced in Section 4.

In this exercise, $\beta_{i,h}^{R}$ captures the average effect of a structural shock across regimes $R = \{tight, loose\}$. It not only captures the effect within a specific regime at the time the shock hits the economy, but also takes into account the effects of regimes changes, which may occur across the projections horizons, since the effects of a shock in period $h = 0, \ldots, H$ are estimated sequentially.

B. *Inference*

Plagborg-Møller and Wolf (2021) show that the local projections coefficients correspond to the reduced-form impulse responses of y_t to the Wold innovations $e_t = y_t - E(y_t|\{y_\tau\}_{\tau<t})$ from a VAR for horizon h. Moreover, the LP residuals $(u_{1,1,t}, ...u_{n,1,t})$ correspond to those same innovations. Consequently, the variance-covariance matrix estimated by local projections contains the same information as the variance-covariance matrix from a VAR. Thus, sign and zero restrictions can be implemented within local projections.[13]

Sign and zero restrictions are implemented by first, estimating the model for each $h = 0, \ldots, H$ and storing the resulting, state-dependent coefficients in $C_h^R = \left[\beta_{1,h}^R, \beta_{2,h}^R, \ldots, \beta_{n,h}^R\right]$. We perform bias correction on the (bootstrapped) estimators, as LP estimates in small samples can be severely

[13] Further feasible identification schemes are long-rung restrictions a la Blanchard and Quah (1989) or narrative sign restrictions as in Antolín-Díaz and Rubio-Ramírez (2018).

biased, as Kilian and Kim (2011) and Herbst and Johannsen (2024) show. Plagborg-Møller and Wolf (2021) demonstrate that structural impulse responses for horizon h can be computed as

$$\Theta_h^R\left(Q, C_h^R, f(\Sigma)\right) = C_h^R f(\Sigma) Q \,.$$

That is, they are a function of the stored LP coefficients as well as $f(\Sigma)$, the lower triangular Cholesky factor of Σ, which denotes the variance-covariance matrix of the one step ahead projection residuals, where $Var(u_{1,1,t}, \ldots u_{n,1,t}) = f(\Sigma)f(\Sigma)'$. The remaining ingredient is an orthogonal matrix Q, where $QQ' = Q'Q = I_n$.

Sign and zero restrictions on the impulse response of variable i at horizon h then can be implemented by randomly drawing Q as in Arias et al. (2018). Permissible draws must meet

$$\begin{aligned} \mathbf{S_k}\boldsymbol{\Theta}^R\left(Q, C^R, f(\Sigma)\right) e_k &\geq 0 \\ \mathbf{Z_k}\boldsymbol{\Theta}^R\left(Q, C^R, f(\Sigma)\right) e_k &= 0 \,. \end{aligned}$$

Note that Q is retained only if it meets the restrictions in both regimes. For example, if all restrictions are met in one regime, but at least one is not satisfied in the other, Q is discarded. The $n(H+1) \times n$ matrices $\boldsymbol{\Theta}^R = \left[\Theta_0'^R\, \Theta_1'^R \ldots \Theta_H'^R\right]$ contain the stacked state-dependent impulse response coefficients. The $n(H+1) \times n(H+1)$ matrices $\mathbf{S_k}$ and $\mathbf{Z_k}$ are constructed as in Rubio-Ramirez et al. (2010) with e_k being the k-th column of the identity matrix I_n.[14]

Finally, inference on the impulse responses is based on percentiles of the permissible draws. Note that the resulting confidence bands do not display estimation uncertainty of the individual draws, but rather describe the distribution of the models, that satisfy the sign and zero restrictions.

C. *Data*

Our sample spans from 1995Q1 to 2018Q4, the period for which detailed information on prudential policies in Europe is available in the MaPPED. We consider the euro area as a single entity. This is helpful for our analyses in that we can more conveniently take into account the common monetary

[14] Although we do not use equality restrictions in our model, we nevertheless present their computation for the sake of completeness.

policy in our estimates.

In the baseline case, we estimate a model with $p = 2$ lags. The vector y_t consists of $n = 5$ variables, namely, real GDP growth, annual growth of nominal loan volumes, the inflation rate, a shadow short rate, as well as a composite lending rate.

We compute year-on-year growth rates of real GDP, nominal loans, and the Harmonized Index of Consumer Prices (HICP), all taken from the ECB data portal. As the HICP is only available from 1997Q1, we extend it backwards to 1995Q1 using the `HICP` time series from the area wide model (AWM) database. Loan volumes are constructed as the sum of nominal outstanding amounts of banks' loans to households and non-financial corporations.

The short-term interest and the composite lending rate enter the model in levels. In order to account for the unconventional policy measures taken by the European Central Bank in the aftermath of the Great Financial Crisis and European debt crisis, we rely on the shadow short rate as proposed in and provided by Wu and Xia (2016) from 2004Q4 onward. The shadow rate is extended backwards to 1995Q1 by using the change in the EONIA.

Finally, the lending rate is derived as the weighted average of interest rates claimed on loans to households and non-financial corporations with weights based on the respective outstanding amounts. As data on bank interest rates are only available from 2003Q1 onward, we backward extend the series with changes in the composite lending rate from Gambetti and Musso (2017).[15]

D. *Identification of Loan Supply Shocks*

As our analyses focus on the propagation of loan supply shocks across regulatory regimes in the euro area, we require a well established procedure to identify appropriate loan supply shocks. Thus, we rely on the identification scheme proposed by Gambetti and Musso (2017), which has been also applied by, e.g. Barauskaitė et al. (2022), Mandler and Scharnagl (2020), or Bijsterbosch and Falagiarda (2015), among others. The identification scheme is based on the dynamics observed in well-established DSGE models. The underlying causes of the disruptions can have a variety of reasons, such as shocks to bank's reserve demand, bank's loss rate or

[15] For an extensive description of their composition of the lending rate as well as the respective sources, we refer the interested reader to the supplementary material (jae2537-sup-0002-Supplementary2.pdf) accompanying Gambetti and Musso (2017).

bank's net worth.[16] In short, loan supply shocks cause real GDP growth, inflation, the short term interest rate, and growth in loan volumes to move in the same direction while the lending rate has an opposite sign.

The identification scheme is shown in Table 1.

Table 1: Sign Restrictions of a Loan Supply Shock

Shock	GDP Growth	Inflation	(Shadow) Short-Rate	Lending Rate	Loan Growth
Loan Supply	+	+	+	-	+

Notes: Identification scheme for expansionary loan supply shocks. The identifying assumptions are imposed on impact, where '+' means an increase and '-' a decrease in the underlying variable.

We now have most of the ingredients for our analysis. What is left is an indicator S_t, which determines the regulatory regime.

4 Determining Regulatory Regimes

The cumulative prudential policy index derived and described in Section 2 contains information on the regulatory stance. That is, it tells us about the regulatory package that is in effect at a given time. In this form, however, no conclusions can be drawn from this as to whether the existing regulatory regime is above or below average.

We therefore decompose the *cPP*-Index into its regulatory trend and cycle using the Hodrick-Prescott filter. This approach requires the choice of a smoothing parameter λ^{HP} that determines the penalization of deviations from the trend. When the smoothness penalty goes to 0, the extracted trend becomes the actual time series. At the other end of the scale, a linear time trend is extracted.[17] While apt values to identify the business cycle have been extensively studied and discussed, there is a lack of an appropriate value to extract a faithful prudential cycle. In order to overcome this gap, we rely on the literature concerning financial cycles.

A. *Prudential Policy and Financial Cycles*

Macroprudential regulation is closely linked to financial cycles. The goal of macroprudential policies is to prevent the build-up of financial imbalances

[16] For a detailed overview of the models considered, see Table II in Gambetti and Musso (2017).

[17] Hamilton (2018) discusses the shortcomings of the HP-Filter and offers a much-noticed alternative which is not suitable for our application due to a lack of observations.

and financial risk. Borio (2014) argues that, in doing so, macroprudential policy should focus on limiting the potential for damage caused by financial instability and hereby address the pro-cyclicality of the financial system head-on. The reason is that peaks in the financial cycle are closely associated with systemic banking crises (e.g. Drehmann et al., 2012; Aikman et al., 2015; Bauer and Granziera, 2017) or financial crisis recessions (e.g. Gourinchas and Obstfeld, 2012; Schularick and Taylor, 2012, among others).

However, a clear value for the smoothing parameter λ^{HP} to extract the financial cycle does not exist and differs depending on the point of view. From a regulatory perspective, the Basel Committee on Banking Supervision (BCBS) recommends in its 2010 "Guidance for national authorities operating the countercyclical capital buffer" to tie the counter-cyclical capital buffer to the credit:GDP-gap, which in turn serves as an indicator for the financial cycle. In order to compute the credit:GDP-gap, the BCBS applies a real-time (one-sided) Hodrick-Prescott filter with smoothing parameter $\lambda^{HP} = 400,000$ on the credit:GDP-ratio. Moreover, the credit:GDP-gap derived in this way has proven to be a reliable leading indicator for financial crises, as Drehmann et al. (2011), Detken et al. (2014), Drehmann and Yetman (2018), or Galán (2019) show.

On the other hand, this value implies a duration of the financial cycle of 30 years, which turns out not to be valid for the euro area. For example, Galati et al. (2016) find the financial cycle for the euro area big-five to vary between ten (Germany and Netherlands), 14 (Italy) and 15 (France and Spain) years. Schüler et al. (2020) and Rünstler and Vlekke (2018) report similar durations for some selected member countries. Taking 17 euro area countries into account, Rünstler et al. (2018) also point to rather medium-term cycles of 13 years, on average. The empirical literature on the duration of financial cycles in the euro area thus implies much lower values for the smoothing parameter. Following Ravn and Uhlig (2002), the smoothing parameter for the financial cycle can be expressed as a function of the length of the business cycle according to

$$\lambda^{HP} = \mathrm{m}^4 \times 1600\,,$$

where m is the multiple of the business cycle duration. Given quarterly data, a standard value of $\lambda = 1,600$ implies a business cycle duration of 7.5 years, which is reasonable for many advanced economies. The financial cycle in the euro area is estimated to be approximately twice as long. Thus, $m = 2$ and the smoothing parameter becomes

$$\lambda^{HP} = 2^4 \times 1600 = 25,600\,.$$

Taken together, a variety of plausible values thus come into question for determining the financial cycle. We take an agnostic approach and extract different regulatory cycles setting the smoothing parameter to

$$\lambda^{RC} = \{25.6, 100, 200, 300, 400\} \times 1000\,.$$

This also serves as a robustness analysis, as it allows us to determine the sensitivity of our results to the choice of the parameter value.

Since regulators make their decisions on the information available at the time of the decision, applying the two-sided HP filter, which uses the entire sample — including future observations — would be corrupted. We therefore use the real-time version of the Hodrick-Prescott filter.

Simply applying λ^{RC} from a two-sided HP filter on the the real-time version harbors distortions. Wolf et al. (2020) show that for a given value of the smoothing parameter, the one-sided HP filter dampens high frequency fluctuations to a greater extend than the two-sided version. That is, it increasingly filters the desired fluctuations with lower values of λ^{RC} and thus, higher frequencies of the cycle. We therefore apply their proposed adjusted one-sided HP filter that overcomes this issue.[18]

Figure 2 shows the resulting regulatory cycles, depending on the underlying value of the smoothing parameter.[19]

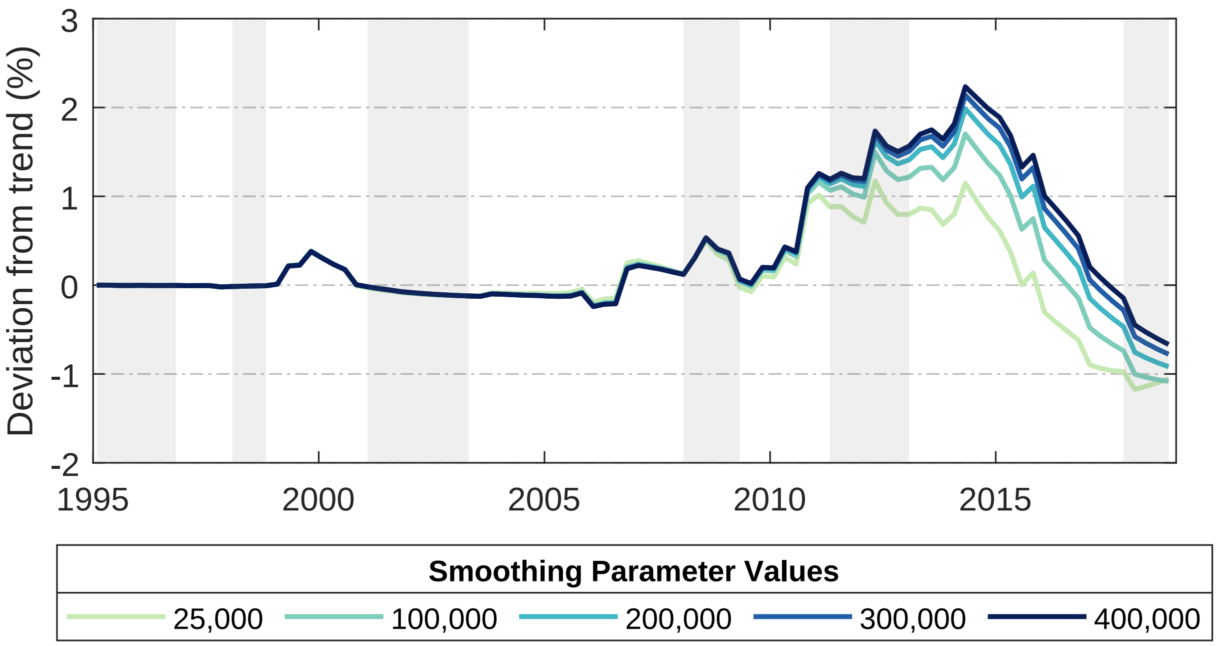
A positive value implies that the actual regulatory stance is above its long-term trend. This means that prudential regulation is tighter than average in a historical context, and vice versa.

[18] For example, a desired cycle from $\lambda = 25,600$ corresponds in their approach to set $\lambda = 10,427.7$ and additionally scale the extracted cyclical component by a factor of 1.073.

[19] In order to validate our statement mentioned at the beginning regarding the relationship between prudential policy making and the financial cycle, we also looked at the leading and lagging properties of the regulatory cycle and the financial cycle in relation to each other. We calculated the latter as the cyclical component of the debt:GDP-ratio using a HP filter with $\lambda = 400,000$. Our analyses show that the regulatory cycle and the financial cycle interact as expected. We measure a high positive correlation between the current state of the financial cycle and future realizations of the regulatory cycle. That is, if the economy is in a state of credit expansion (debt:GDP-ratio is above its long-term trend), prudential regulation in the future will also be disproportionately tight, i.e. above its long-term trend. We also find a high negative correlation between the current regulatory cycle and the future debt:GDP-gap.

Up to 2011, the different λ^{RC} identify an almost identical cycle. From 2011 onward, however, three differences emerge, depending on the assumed frequency for the regulatory cycle. First, the higher the frequency, and thus the lower the value of λ^{RC}, the shorter the phase of comparatively tight regulation that begins in 2011. Secondly, the historical extent of the tightening is assessed differently. When the frequency of the regulatory cycle is high, the GDP-weighted cPP-Index is at most one point above its long-term trend in the years between 2011 and 2015. If the frequency is slowed down, the difference rises to more than two points. This means that the historical extent of tightening changes noticeably. Third, with higher frequency, a phase of relative easing is reached sooner.

Figure 2: Regulatory Cycles



Notes: Cycles from the GDP-weighted cumulative Prudential Policy-Index extracted using the one-sided HP-filter. The cycles vary depending on the value of the underlying smoothing parameter. Grey bars mark OECD based recession indicators for the euro area.

The extracted cycles form the basis for analysing state-dependent effects, as they are the indicator variable for calculating a transition function.

B. *Smooth Regime Transition*

In order to allow for smooth transitions between the regulatory regimes, we follow Granger and Teräsvirta (1993) and compute the state-variable S as a logistic transition function of the form

$$S\left(rc_{t-1}\right)=\frac{\exp\left(\kappa\frac{rc_{t-1}-\mu}{\sigma_{rc}}\right)}{1+\exp\left(\kappa\frac{rc_{t-1}-\mu}{\sigma_{rc}}\right)}\in[0,1]\,. \tag{4.1}$$

Thus, S is a smooth increasing function of the indicator variable rc, the regulatory cycle with underlying parameter value $\{25.6, 100, 200, 300, 400\} \times 1000$. We use the lagged value of the indicator variable in order to avoid endogeneity between the loan supply shock and the regulatory regime. The main reason is that a loan supply shock can alter the prudential landscape. For example, if the dynamics caused by the loan supply shock lead to changes to capital requirements or the loan-to-value ratios applicable to enterprises and households. Such regulatory adjustments would clearly be captured by the state variable which, in turn, inevitably results in endogeneity problems.[20]

The share that the economy is in a particular regime is determined by μ. In our case, μ is specified by the share that the economy spends in a loose regime and varies depending on the smoothing parameter.[21] σ_{rc} is the sample standard deviation of the indicator variable. The vehemence of the regime change is determined by κ: the higher the selected value for κ, the more abrupt the change. We follow the standard literature and set $\kappa = 5$ to generate an intermediate intensity of regime changes.

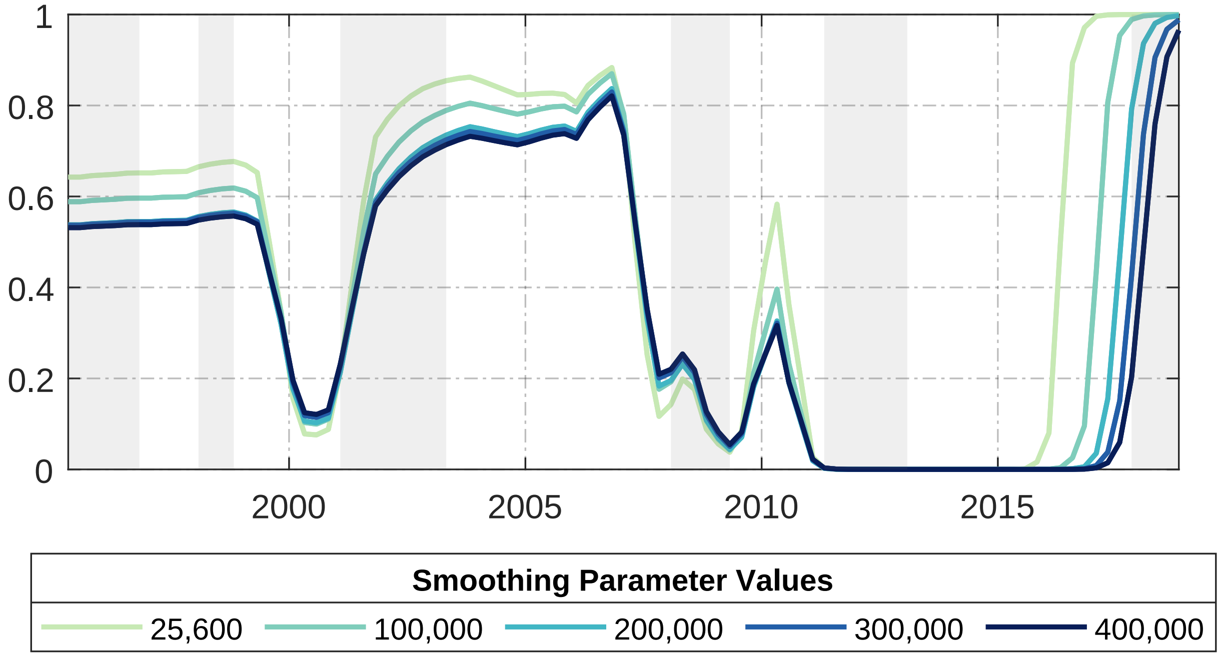
The resulting state-variables are depicted in Figure 3. They reflect the weights of the regimes that are assigned to the economy in the corresponding periods. A value close to one implies that the economy is in a relatively loose regime, and vice versa. Accordingly, prudential regulation in the euro area was comparatively tight shortly after the turn of the millennium and in the years following the financial crisis and the subsequent crisis years. Depending on the frequency assumed for the regulatory cycle, prudential regulation becomes comparatively loose sooner (relatively high frequency) or later (relatively low frequency).

Given that the time at which the economy is once again in a loose regime varies at the end of the sample depending on λ^{RC}, and that at the same time there is no unique value for lambda that extracts a regulatory cycle beyond

[20] This is also another reason why we consider the announcement date of the policy measures when setting $m^k_{i,t}$.

[21] The parameter takes the values 56 when $\lambda^{RC} = 25{,}000$, 51 when $\lambda^{RC} = 100{,}000$, 48 when $\lambda^{RC} = 200{,}000$, 47 when $\lambda^{RC} = 300{,}000$, and 46 when $\lambda^{RC} = 400{,}000$.

Figure 3: STATE-VARIABLES



Notes: Transitions functions based on the regulatory cycles derived from the GDP-weighted cumulative Prudential Policy-Index. Grey bars mark OECD based recession indicators.

doubt, we conduct our analysis below as follows: We first estimate a model for the period 1995Q1 to 2015Q1. The latter corresponds to the point in time up to which no change in trend towards a looser regime is identified across all values for λ^{RC}. These results represent our baseline results. We then estimate our model for the entire sample. This adds observations for both regimes. However, as λ^{RC} increases, the tighter regime gets disproportionately more observations and vice versa.

5 Loan Supply Shocks, Prudential Regulation, and the Business Cycle

This section discusses the role of the regulatory regime for the business cycle effects of expansionary loan supply shocks. Furthermore, we analyze possible asymmetries in the propagation.

A. *Baseline Results*

What role does the prudential regime play in the business cycle effects of loan supply shocks? Figure 4 shows the state-dependent impulse responses to an expansionary loan supply shock across regulatory regimes. Solid lines represent the baseline median responses. The surrounding dark (light) areas demarcate the space between the 16th (5th) and the 84th (95th) percentiles.[22]

First, we examine the effects in the tight regime given the short sample, which covers the period 1995Q1 until 2015Q1. The responses to be considered are depicted in red.

Accordingly, expansionary loan supply shocks lead to significant effects in the first year after they occur. After an initial increase of 0.2 percentage points, output grows at about the same rate in the following two quarters. This is also true for inflation and credit growth, which increase at a similar rate and over roughly the same period of time. As a consequence, the central bank increases the short-term interest rate in order to curb the business cycle. This induces the lending rate, after an initial fall, to turn positive. This immediate reversal effect is also found in Mandler and Scharnagl (2020), Gambetti and Musso (2017) or Bijsterbosch and Falagiarda (2015), among others. For all variables, the peak of the expansionary effect is measured within the first year after the shock hits the economy.

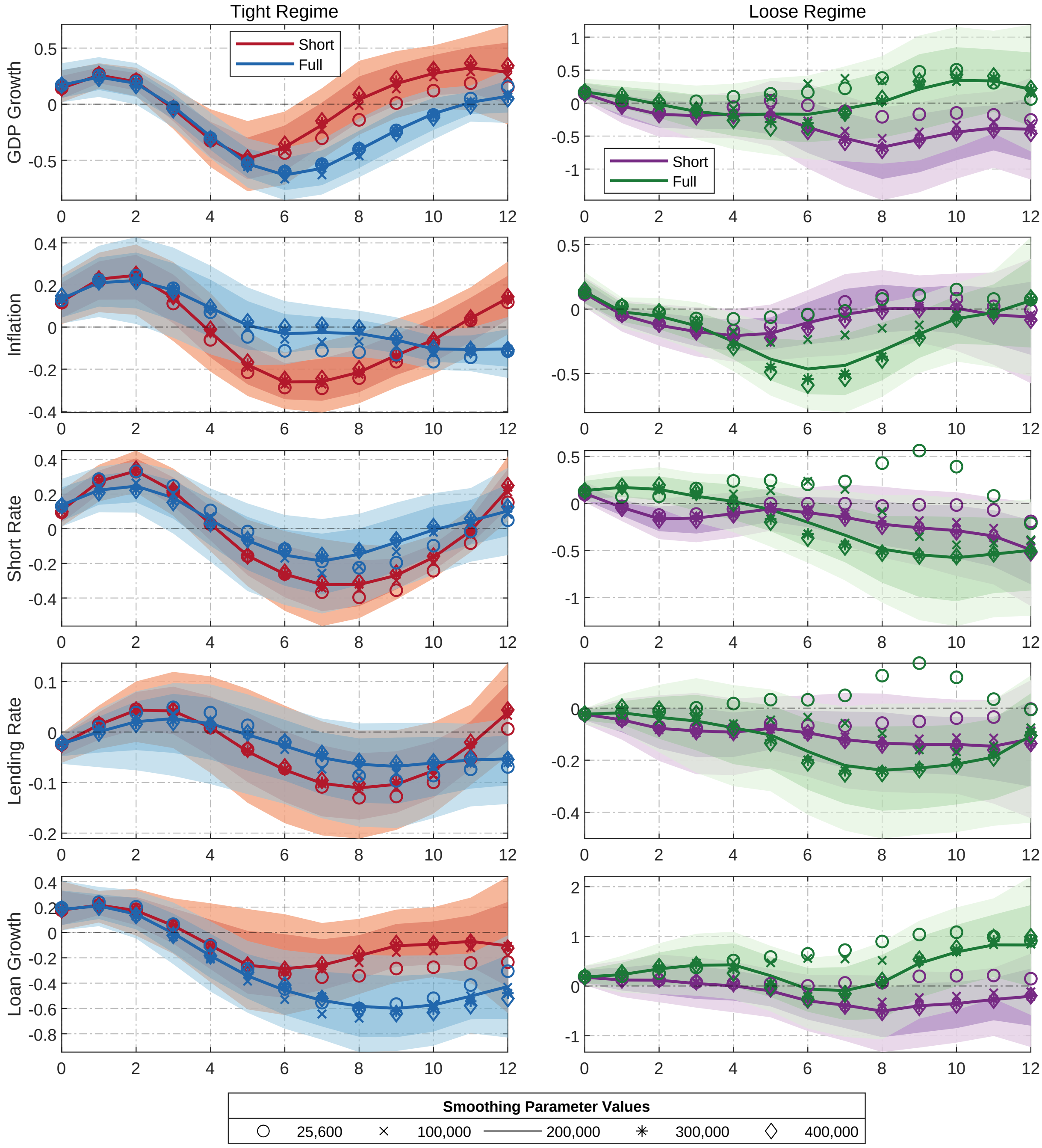
The expansionary effect turns into a bust phase after about one year. All the variables considered show negative growth or changes, which are significant at least at the 68 percent level. All quantities reach their trough within the second year. The pattern is found regardless of the choice of the value for the smoothing parameter used in order to extract the regulatory cycle.

Extending the time frame to the entire sample (blue) confirms the central finding that expansionary loan supply shocks lead to a business cycle characterised by a boom-bust swing. What is striking is that, with the exception of the impulse responses of inflation, the remaining median impulse responses are very similar for the first four to six quarters after the shock hits the economy.

A closer look at the impulse responses from the varying samples reveals that the most pronounced differences are found in the response of output, inflation and loan growth. The deviations in the median responses between the samples is up to 0.5 percentage points, with the negative effect being stronger in the full sample. Inflation, on the other hand, does not exhibit the pronounced bust cycle, but returns to and remains at the zero line. Loan growth, a key factor for prudential activities, follows the same pattern

[22]For the sake of comparability, the median responses from the linear model are shown in section B of the appendix. In the linear specification, we estimate equation 3.1 with the lag structure as well as the choice of variables as in the state-dependent case. The results are shown in Figure B.1.

Figure 4: Impulse Responses Across Regimes, Short Vs. Full Sample



Notes: State-dependent impulse responses to an expansionary loan supply shock. Identifying assumptions are impose on impact. Lines and markers depict median responses in tight (left panel) and loose (right panel) regulatory regimes. Red (blue) lines and markers depict median responses in the tight regime from the short (full) sample spanning the period 1995Q1 until 2015Q1 (2018Q4). Purple (green) lines and markers depict median responses in the loose regime from the short (full) sample spanning the period 1995Q1 until 2015Q1 (2018Q4). Smoothing parameter values relate to the smoothing parameter λ^{RC} used in order to extract regulatory cycles, as described in the main text. Dark (light) areas depict corresponding 68% (90%) probability masses.

as output. This is in line with Jordà et al. (2016), who show that private borrowing is strongly pro-cyclical in advanced economies. In the first

1.5 years after the shock, we find a pronounced boom-bust phase. Looking at the entire sample, however, the bust phase lasts longer. Loan growth now reaches its trough at -0.6 percentage points at $h = 9$, i.e. after more than two years. And negative loan growth in the tight regime can also be observed in the periods thereafter. As with GDP growth, the difference in median responses across the samples is up to 0.5 percentage points (for $h = 9$).

Looking at the effects of expansionary loan supply shocks in a loose regulatory regime, the responses do not provide such a consistent pattern. The responses from the short sample (purple) indicate very short-lived effects of the shock. All variables except for the lending rate are already insignificant in the first quarter after the shock occurs.[23] That is, a clear boom phase cannot be observed. Rather, the economy tends to move directly into a recessionary phase. Even if the median responses are significant in the fewest cases, this tendency is counter-intuitive. The impulse responses show this pattern regardless of the λ-value used to determine the underlying regulatory cycle. However, it is striking that the responses produced by a setup with $\lambda^{RC} = 25,600$ (purple circle) are always above the other responses. While this discrepancy is barely noticeable in the short sample, it becomes striking when all observations are taken into account. Depending on which variable is considered, the responses from the full sample differ to a greater or lesser extent. Output, inflation, the lending rate, and credit growth are confirmed at least for the first four to six periods after the shock. After that, they tell a different story, especially in the case of output, inflation, and loan growth.

For instance, output is on a positive growth path in the third year after the shock. This development is similar to the response of output from the short sample in the tight regime. The same applies to the reaction of inflation. More decisive from a prudential perspective is the reaction of loan growth in the loose regime when looking at the entire sample. The responses from the models with $\lambda^{RC} \geq 200,000$ already indicate a moderately positive path of loan growth. However, this is insignificant in all but the third year, which is consistent with the positive output growth path, rising inflation and negative interest rates over the projection horizon. However, assuming a higher frequency for the regulatory cycle i.e. a lower value for λ^{RC}, loan growth moves along a noticeably positive

[23]Per construction, the initial responses are identical in both regimes.

growth path over the entire projection horizon. Thus, unlike in the tight regime, the results are sensitive to some extent to the choice of the smoothing parameter. From a regulatory perspective, this is particularly problematic in the case of loan growth (and output), as prudential regulation is closely linked to its development.

With this limitation in mind, we now examine whether asymmetric effects can be detected.

B. *Are the Responses Asymmetric?*

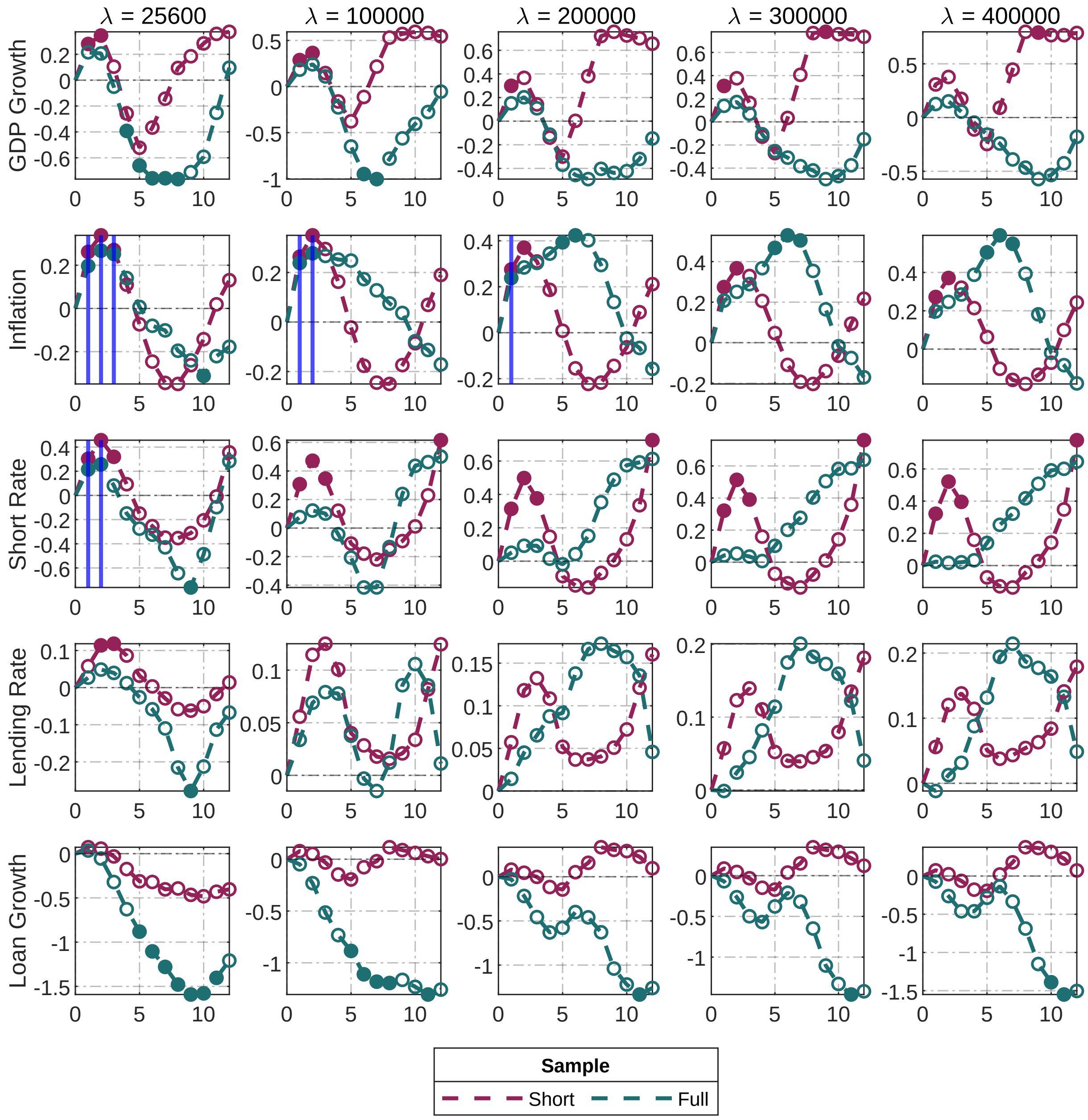
Have loan supply shocks similar business cycle effects across regulatory regimes? To answer this question, we estimate $\beta_{i,h}^{tight} - \beta_{i,h}^{loose}$ for each variable i and horizontal h as well as the corresponding percentiles.[24] Figure 5 shows the results. The magenta (cyan) lines represent the median differences from the model with the short (full) sample. For ease of reading, we add a filled dot for each difference that is significant at the five percent level. The vertical blue lines highlight the periods where both models indicate significant state dependence.[25]

If a rather high frequency, i.e. $\lambda^{RC} = \{25.6, 100, 200\} \times 1,000$, is assumed for the regulatory cycle (columns $1-3$), significant differences in the responses of inflation appear in both samples, as shown by the blue lines. The lower the value of λ^{RC} — and therefore the higher the frequency of the regulatory cycle — the more periods within the first year after the onset of the shock show significant differences. More precisely, in the tight regime inflation reacts more strongly. This finding is interesting from a monetary policy perspective, as it implies that the central bank would also have to react state-dependently to the developments triggered by the loan supply shock — which she does, as can be seen from the reactions of the short-term interest rate. However, the difference in the responses also comes about because inflation in the loose regime becomes deflationary

[24] It is quite conceivable that in a tight regime, expansionary loan supply shocks have more muted effects than contractionary loan supply shocks – and vice versa in the case of loose regulatory regimes. In order to investigate this possibility, expansionary and contractionary shocks would have to be analysed separately. One possibility would be to decompose an identified loan supply shock into its positive (expansionary) and negative (contractionary) components and compare their effects for given states, e.g. as in Finck and Rudel (2022) or Tenreyro and Thwaites (2016). However, this approach leads to inconsistency, as asymmetry is being imposed on a shock from a linear model. We also have too few observations to divide our sample accordingly. Therefore, when we talk about asymmetry in the following, this refers exclusively to the differences in the effects between the regulatory regimes. Since we are dealing with a linear model, asymmetric responses to an expansionary loan supply shock are the mirror image of the responses to a contractionary shock.

[25] The corresponding full results are shown in Figures C.3 and C.4 in the appendix.

Figure 5: Difference in Responses



Notes: Difference between the impulse responses from the tight and loose regime ($\beta_{i,h}^{tight} - \beta_{i,h}^{loose}$). The magenta (cyan) dotted lines represent the median differences from the short (full) sample. Filled dots indicate projection horizons with significant asymmetry at the 5% level. Blue bars emphasise horizons in which there is significant asymmetry in both samples.

from $h = 2$, as already seen in Figure 4. Since this development seems rather counter-intuitive, the findings must be taken with a grain of salt.

In the case of the truncated sample, we also find significantly state-dependent responses of output within the first year after the occurrence of the shock. This finding holds across all calculated regulatory cycles. Taken in isolation, this suggests that the loan supply shock is stronger in the tight regime. We find no significant state dependence in the response of loan growth.

Looking at the entire sample, we find significant state dependence for models with low values of the smoothing parameter λ^{RC}, especially for GDP and loan growth rates in the course of the second year. Figure 4 reveals that the state dependence arises because (i) in the tight regime, the economy is in a recessionary phase during that projection horizon, while (ii) in the loose regime, at the same projection horizon, the loan supply shocks cause output and loans to take a positive growth path. For high values of λ^{RC}, which correspond to slow moving regulatory cycles, we cannot identify any significant state dependencies, except for the already mentioned state dependencies of inflation.

To summarise, the reactions in the tight regime are independent of the choice of the smoothing parameter λ^{RC} for determining the regulatory cycle. That is, here we find quite robust results concerning the effects of expansionary loan supply shocks on the business cycle. All reactions are characterised by a considerable boom-bust cycle. In the full sample, the bust cycle lasts longer. In the loose regime, on the other hand, we find different responses depending on the frequency of the prudential cycle as well as the observation period considered. While all responses are relatively similar in the first year after the onset of the shock, we find some considerable contrasts in the subsequent projection horizons.

Against the background of the relevance of credit developments for prudential regulation, we want to discuss the reactions of loan growth in more detail. In the short sample, loan growth responds only marginally to the expansionary loan supply shocks. This applies to both regimes and all smoothing parameters, resulting in no asymmetry whatsoever, as can be seen in Figure C.3. This changes when all observations are taken into account. In the tight regime, a short period of loan expansion is followed by a phase of negative credit growth. The result applies regardless of the cycle frequency assumed. In the loose regime on the other hand, the basic tenor across all regulatory cycles frequencies is that an expansionary loan supply shock tends to causes persistent loan growth. Particularly when the regulatory cycle has a high frequency, an expansionary loan supply shock triggers sustained positive credit growth. As output shows no notable reaction, we measure a positive growth differential between loans and output, which increases in the course of the projection horizon. Thus, in such a regime, credit-driven growth — originating from the private sector — occurs. Thus, we find evidence that loose prudential regulation is more likely to foster an enduring build-up of private borrower's credit after an expansionary credit supply shock as against a tight regulatory regime. Jordà et al. (2016) report that such credit booms have the potential to make recessions and recoveries worse and increase the probability of financial crisis.

This result should, however, be treated with caution. Our approach yields robust results on the effects of expansionary loan supply shocks on the business cycle when prudential regulation is relatively tight. But not if the regulatory stance is below its trend. Why is that?

C. *The Impasses of Determining Loose Regimes*

The historical development of prudential regulation plays an integral role in this. With a few exceptions, prudential regulation has followed a path over the entire sample that is mainly characterised by tightening, as can be seen in Figure 1. This rather unidirectional development is also reflected in the course of the cumulated Prudential Policy index. The consequence is, on the one hand, that the regulatory trend, no matter by which means one determines it, is rising over almost the entire sample. This ensures that we have a good understanding of what a relatively tight regime is, i.e. when prudential regulation is above its long-term trend. However, since this trend is ascending the majority of the time, even loose periods are tighter by historical standards than past periods of loose regulation. Therefore, the extracted loose regimes cannot be clearly distinguished as such. They are merely to be understood as less tight regimes rather than actually looser regulatory conditions.

Another difficulty concerns the choice of the smoothing parameter λ^{RC}. As can be seen in Figure 3, there are different assignments of when the economy turns into a state of relatively loose regulation, especially towards the end of the observation period. With increasing values of λ^{RC}, the point in time, at which $S(rc_{t-1}) > 0.5$, shifts to the end of the observation period. As a result, with increasingly low frequency of the regulatory cycle, more and more observations are assigned to the tight regime.[26] In our case, this leads to more robust results of the responses in the corresponding regime. In

[26] Recall how the share the economy spends in the loose regime, μ, decreases with the increase in the smoothing parameter value λ^{RC}.

combination with the already described difficulty to separate loose regimes as well as our relatively short observation period, this leads to our results being more dependent on the choice of the smoothing parameter in the loose regime.

Therefore, additional observations of periods of persistent prudential loosening are needed to allow us to make more accurate conclusions about the role of a loose regulatory regime for the business cycle effects of expansionary loan supply shocks.

6 Robustness

In this section we put our results to the tests by performing a number of sanity checks. First, we estimate our model using a purified regulatory cycle in order to rule out that our regulatory cycle is driven by the business cycle. Next, we use the unweighted version of the cumulative prudential policy index in our empirical model. Finally, we incorporate state-variables that are derived from the empirical cumulative density function of the underlying indicator variable. In all exercises, we utilise the full sample to take into account all available observations.

A. *Purified Regulatory Cycle*

Especially for low values of the smoothing parameter λ, it may be that the identified regulatory cycle is heavily driven by the business cycle. The reason is that we use a high-pass filter to extract the cycles. This allows fluctuations in the high frequency range to pass into the identified cycle almost without dampening. The business cycle is such a (relatively) high-frequency cycle. Therefore, one could argue that our impulse responses represent the reactions to an expansionary loan supply shock over the business cycle in the euro area, rather than over the regulatory cycle. To avoid this bias, we cleanse our regulatory cycle from the business cycle. To do this, we regress each of the regulatory cycles, rc, derived in Section 4 on the business cycle, bc, as well as a trend τ, and a constant c, i.e.

$$rc_t = c + \delta * bc_t + \tau + u_t \ .$$

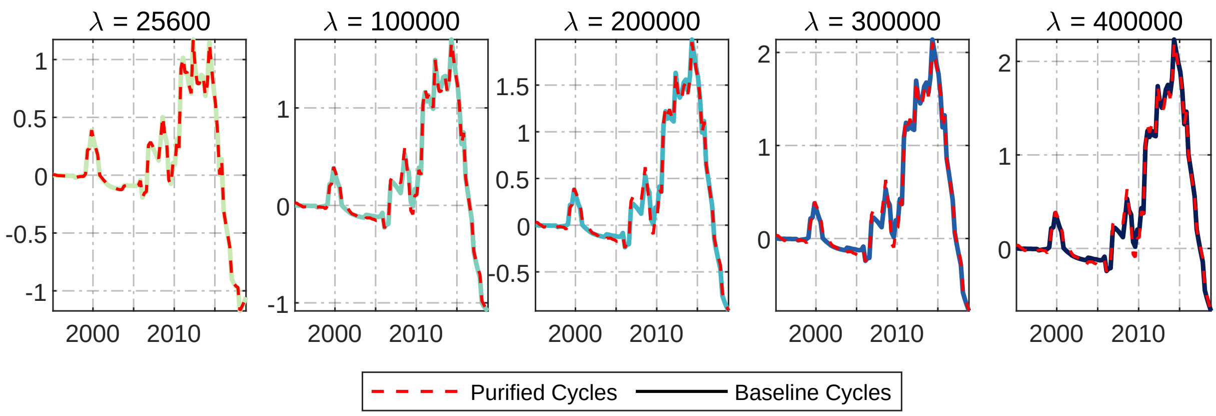
To calculate the business cycle, we rely on an established method and filter the natural log of real GDP by means of a two-sided HP filter with smoothing parameter $\lambda = 1,600$.[27] The purified regulatory cycle, $\tilde{rc}$, is then the difference between the original regulatory cycle and the estimated contribution of the business cycle, i.e.

$$\tilde{rc}_t = rc_t - \hat{b} * bc_t \ ,$$

which then represents our state indicator.[28]

The purification process only slightly alters the development of the regulatory cycle, as can be seen in Figure 6. If any, deviations from the baseline cycles (solid lines) are only detectable in homeopathic doses for cycles extracted by a high smoothing parameter. That is, our regulatory cycles are not driven by the business cycle in the euro area. Consequently,

Figure 6: Purified Regulatory Cycles



Notes: Regulatory cycles purified from the business cycle. Smoothing parameter values λ correspond to the frequency of the regulatory cycle. In all cases, the business cycle is extracted by applying the two-sided HP-filter with smoothing parameter value 1,600 on the natural log of real GDP.

the impulse responses from this robustness exercise are consistent with the results found so far, both in the tight (Figure 7) and loose (Figure 8) regimes.

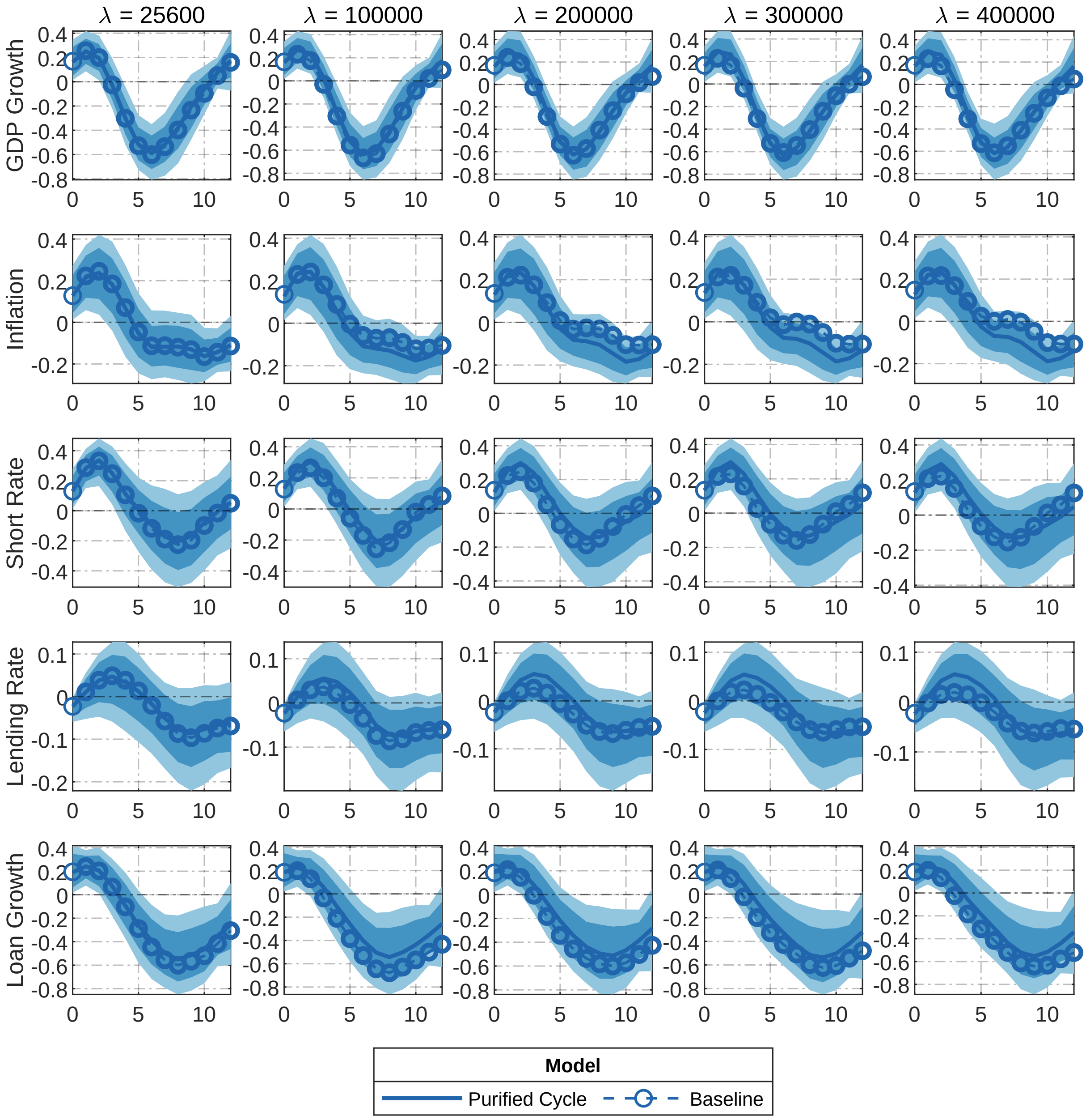
B. *Re-weighting: Loan Volumes*

In our baseline model, we compute the cumulative prudential policy index for the euro area based on GDP-weighted country-specific prudential policy

[27] Hamilton (2018) discusses the shortcomings of the HP-Filter and offers a much-noticed alternative which is not suitable for our application due to a lack of observations.
However, Schüler (2019) shows that Hamilton's approach comes with similar flaws as the HP-filter.

[28] It should be noted that this approach introduces uncertainty on three dimensions. Firstly, there is some level of uncertainty in the computation of the regulatory cycle, as the true smoothing parameter is latent. The same is true for the computation of the business cycle, which is the second source of uncertainty. Lastly, there is estimation uncertainty in the regression of the regulatory cycle on the business cycle.

Figure 7: Purified Regulatory Cycle (Tight Regime)

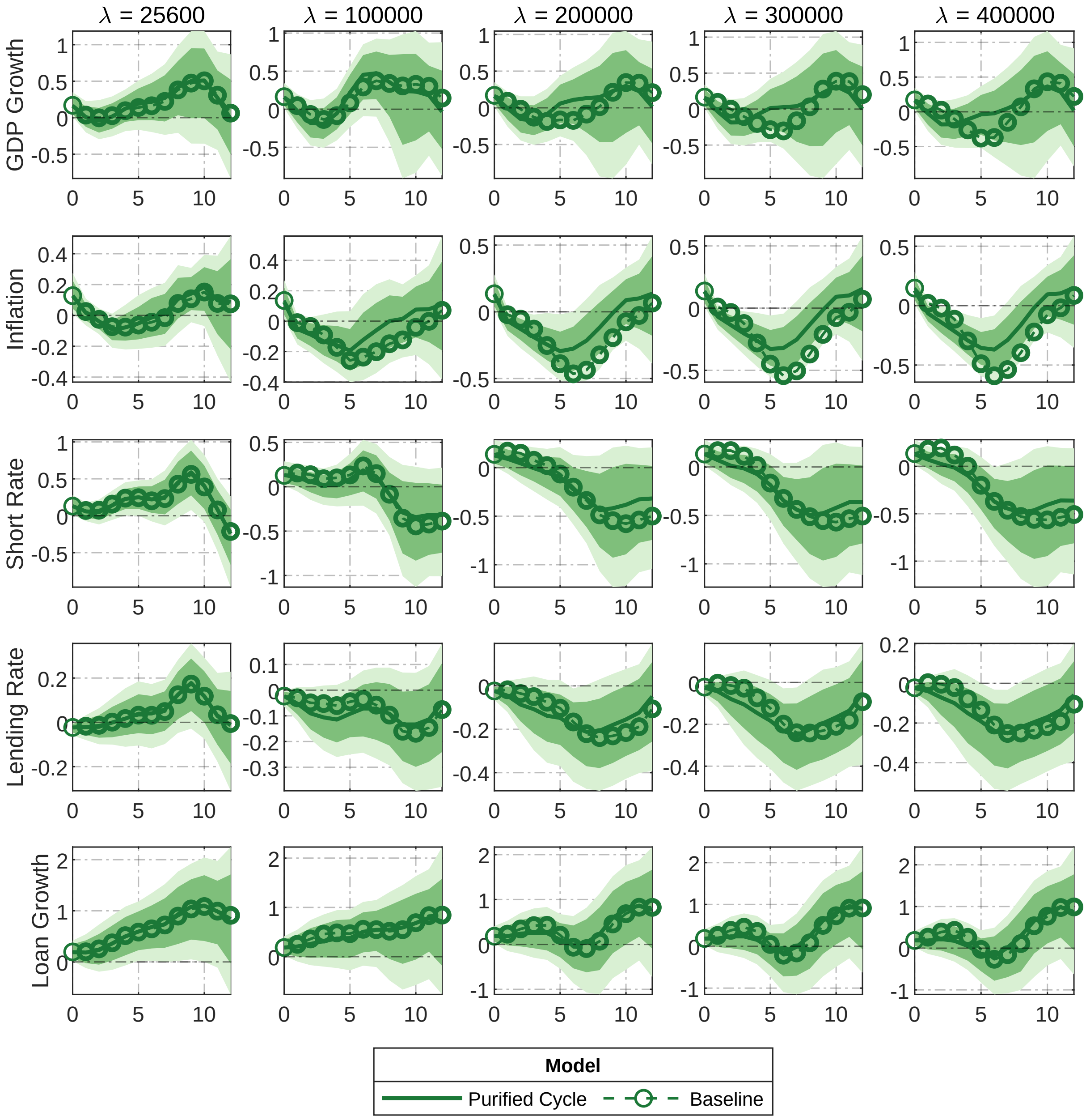


Notes: State-dependent impulse responses to an expansionary loan supply shock in a regulatory tight regime. Solid lines represent median responses from the models with purified regulatory cycle. Dashed lines depict median responses from the corresponding baseline model. Projection horizons in which the median from the baseline model significantly deviates at the 5% level from the alternative model are shown by shaded circles. Dark (light) areas depict 68% (90%) probability masses.

indexes, *iPPI*. The rationale behind this is to assure that our cumulative index is not driven by prudential policies introduced by rather small countries to the same extent as, say, one of the four large member states.

However, there are countries that are relatively small economically but have a sizeable financial sector. Their regulatory measures are therefore likely more relevant than prudential measures in countries where the

Figure 8: Purified Regulatory Cycle (Loose Regime)

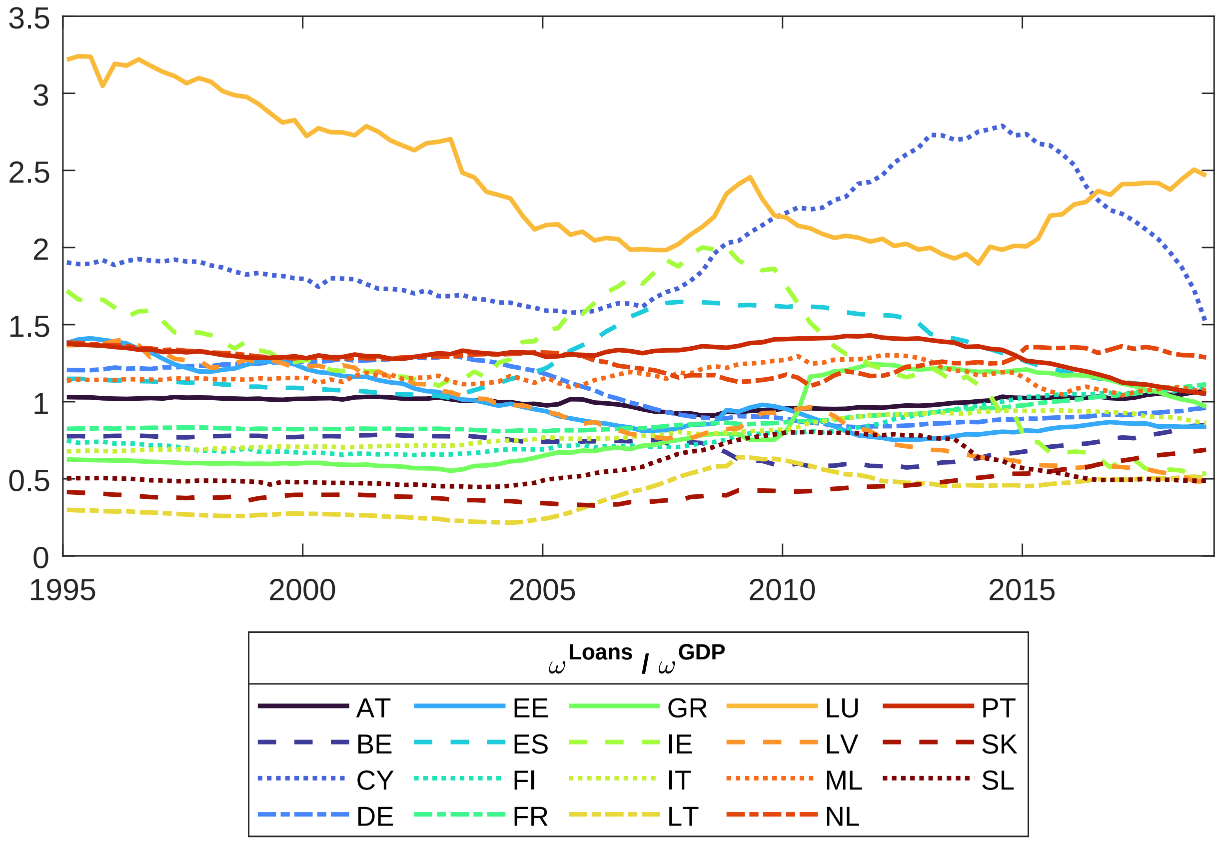


Notes: State-dependent impulse responses to an expansionary loan supply shock in a regulatory loose regime. Solid lines represent median responses from the models with purified regulatory cycle. Dashed lines depict median responses from the corresponding baseline model. Projection horizons in which the median from the baseline model significantly deviates at the 5% level from the alternative model are shown by shaded circles. Dark (light) areas depict 68% (90%) probability masses.

financial sector is not as prominent.

To take this into account, we re-weight the country-specific measures with the share of the total nominal loan volume that the country has at the given time. The changes in the country's influence are indicated in Figure 9. It depicts the ratio between the loans-weight and GDP-weight for each country. A ratio above one implies that the weighting based on loan volume is higher than the country's GDP weighting. Values below one indicate that the country loses leverage in the corresponding periods with the new weighting. Hence, regulatory measures taken by Luxembourg, Cyprus, and Ireland are now much more weighty, while Lithuania, Slovakia, and Slovenia are contributing less to the euro area cumulative prudential policy index.

Figure 9: Loans-weight to GDP-weight

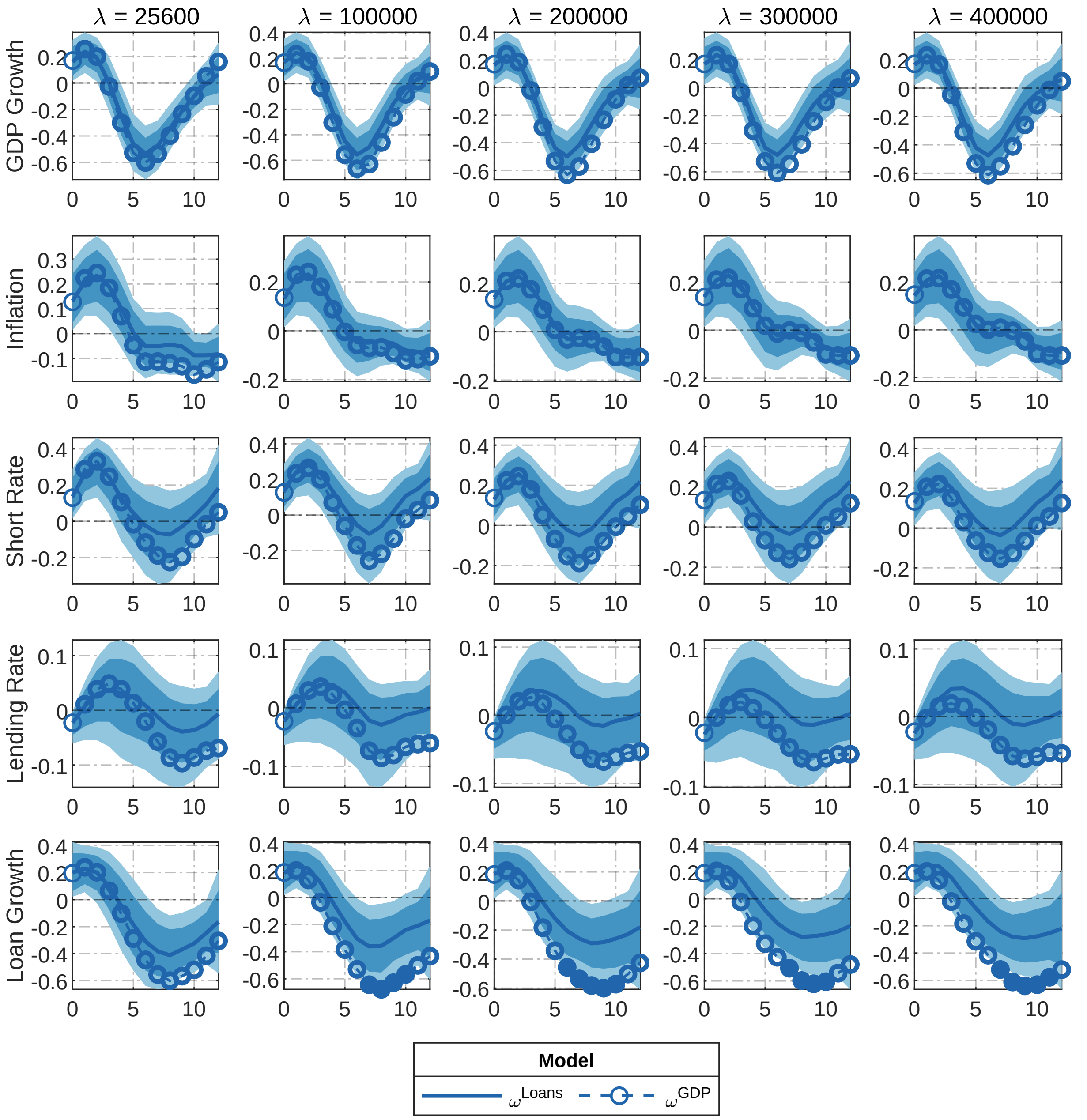


Notes: Ratio between country's loans weight and GDP-weight.

The business cycle effects of a loan supply shock in this setup barely differ from our baseline results, as Figure 10 shows. The most obvious deviation is the more muted reaction of loan growth. In particular, if a low frequency is assumed for the regulatory cycle ($\lambda^{RC} \geq 100{,}000$), the deviation from the base model is significant, as indicated by the colored dots. The bust phase of output is also more muted. However, the differences are not significant. Overall, we again see robust results for the tight regime.

Again, in the loose regime, we find the most apparent divergence from the baseline model in the response of loan growth, especially when a slower moving regulatory cycle is assumed. As can be seen from Figure 11, in this constellation loan growth follows a boom-bust cycle, similar to the response

Figure 10: Loans-weighted cPPI (Tight Regime)

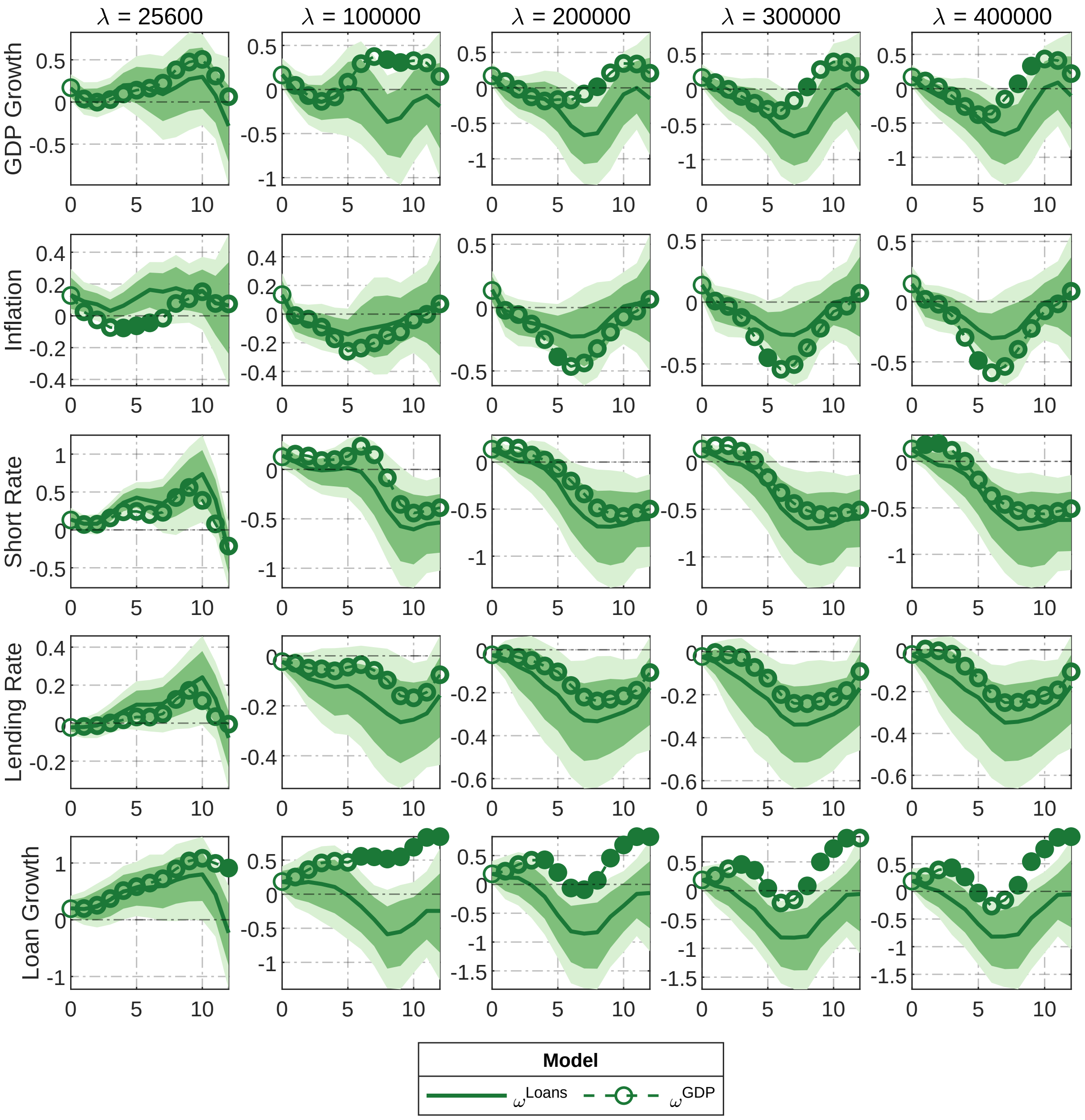


Notes: State-dependent impulse responses to an expansionary loan supply shock in a regulatory tight regime. Solid lines represent median responses from the models with regulatory cycles based on the loans-weighted cPP-index. Dashed lines depict median responses from the corresponding baseline model with weights based on a country's GDP. Projection horizons in which the median from the baseline model significantly deviates at the 5% level from the alternative model are shown by shaded circles. Dark (light) areas depict 68% (90%) probability masses.

of output. In this exercise, we cannot confirm that expansionary loan supply shocks lead to sustained loan growth.

However, it must be said that analysis suffers from data availability. Reliable data on national credit volumes are available for most countries from 2003Q1 at the earliest. With so few observations, we would not have

Figure 11: Loans-weighted cPPI (Loose Regime)



Notes: State-dependent impulse responses to an expansionary loan supply shock in a regulatory tight regime. Solid lines represent median responses from the models with regulatory cycles based on the loans-weighted cPP-index. Dashed lines depict median responses from the corresponding baseline model with weights based on a country's GDP. Projection horizons in which the median from the baseline model significantly deviates at the 5% level from the alternative model are shown by shaded circles. Dark (light) areas depict 68% (90%) probability masses.

been able to meaningfully estimate the number of unknown parameters. In order to backwards extend the data to 1995Q1, we have used the weights from the first quarter for which data was available for the missing periods.

To further investigate the robustness of our results with regard to the cumulative prudential policy index, we estimated our model with an unweighted index as the next stress test.

C. *Unweighted Cumulative Prudential Policy Index*

The cumulative prudential policy index is the basis for identifying regulatory cycles and is therefore essential for our results. In order to avoid distortions due to the choice of country weightings, we derive our regulatory cycles from an unweighted index in the following. At the same time, this means that each country and each measure contributes equally to the cPPI. All other settings remain unchanged.

Figure 12 shows the state-dependent median impulse responses from this exercise. The solid lines depict the median responses from the setup with unweighted policy indexes. Dashed lines are the median responses from the baseline model.

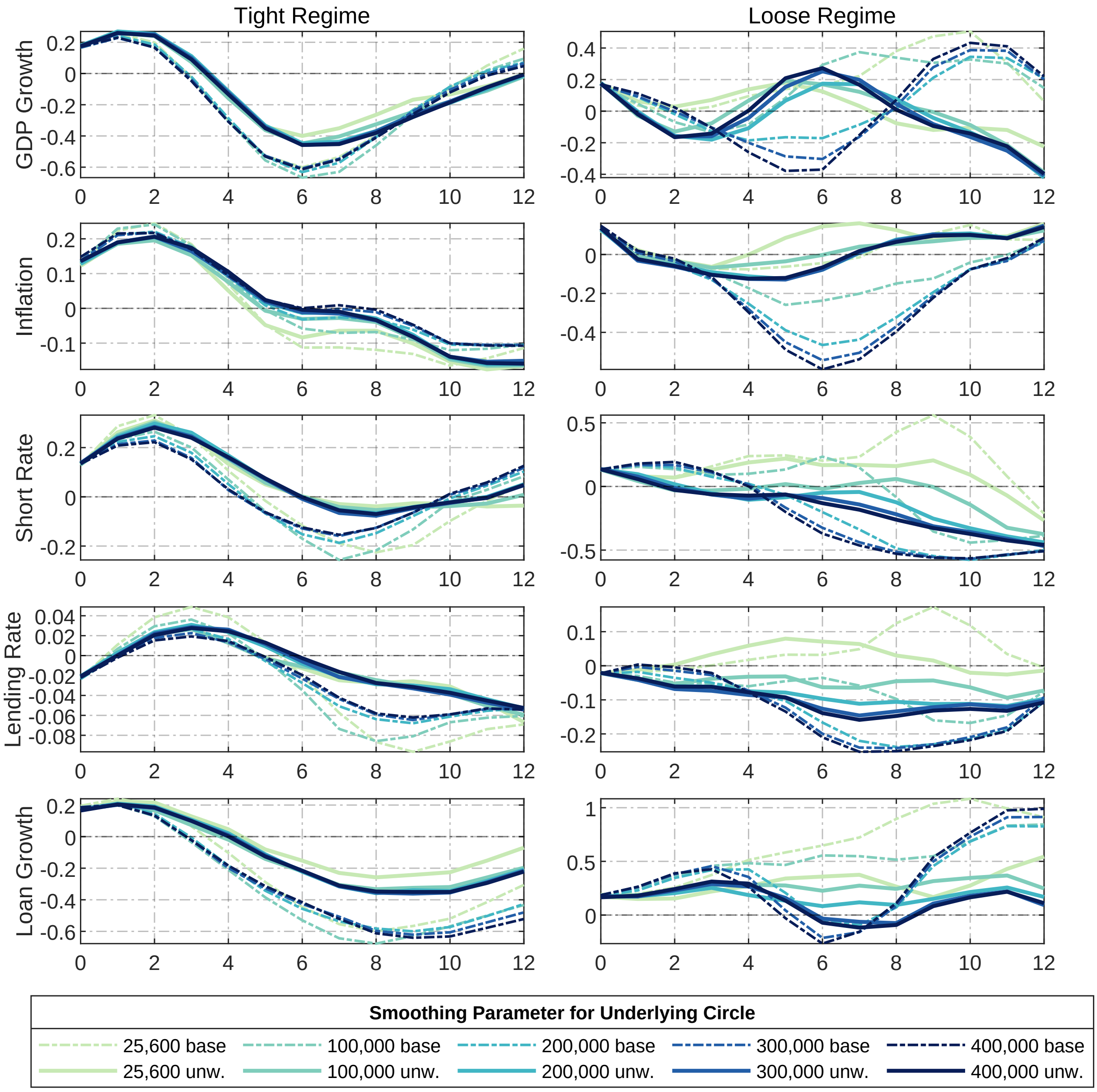
In both regimes, our results are overwhelmingly confirmed with the use of the unweighted index. As before, our results from the tight regime are strongly confirmed. Here, for a given value of λ^{RC}, the median response from the baseline model tends to be below the median response from the alternative specification. As Figure 13 shows, the median responses from the baseline model are within the range of the variation in $\beta_{i,h}^{tight}$ from the alternative specification. However, the general dynamics that expansionary loan supply shocks in the euro area cause remain unchanged.

In this analysis, too, the responses in the loose regime give a diffuse picture, as they differ in part significantly with the choice of the smoothing parameter value used to determine the regulatory cycle. In particular, the responses of inflation in the loose regime deviate from the results of the baseline model as the value of the smoothing parameter increases, as Figure 14 shows. Nevertheless, for the vast majority of projection horizons, the results from our baseline model lie within the confidence range of the alternative specifications.

D. *Regime Determination via Empirical Cumulative Density Function*

In our baseline model, we generate an intermediate intensity of regime changes by setting $\kappa = 5$ in the logistic transition function equation (4.1). Although this value is standard in the literature (e.g. Ascari and Haber, 2022), we test our results for robustness by replacing the logistic function with an transition function based on the empirical cumulative density

Figure 12: Unweighted vs. GDP-weighted cPP



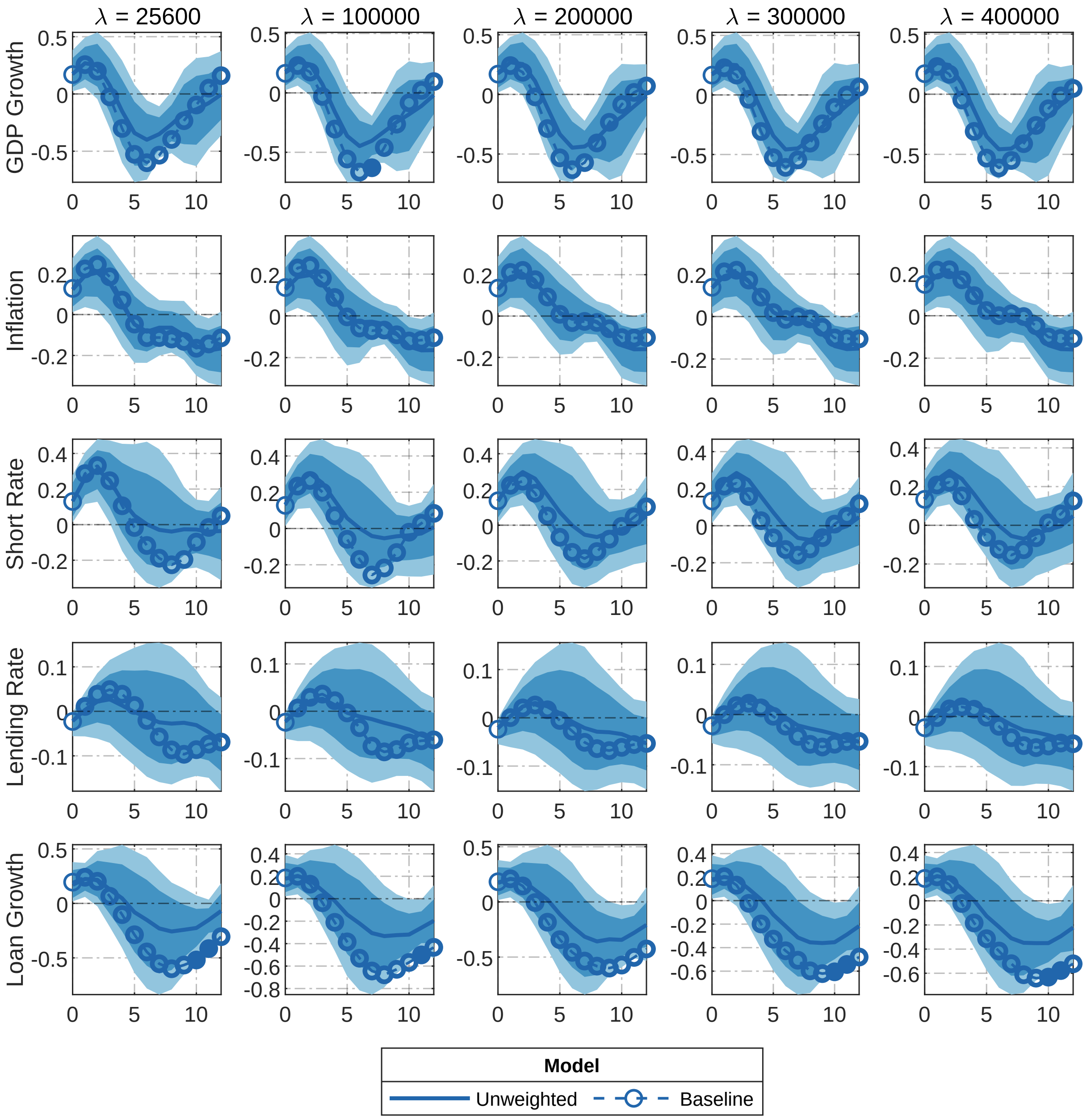
Notes: State-dependent impulse responses to an expansionary loan supply shock. Regulatory regimes are derived from the unweighted cumulative Prudential Policy (cPP) Index. Resulting median impulse responses are depicted by solid lines. Dashed lines report the median responses from the baseline model with states derived from the GDP-weighed cumulative prudential policy index.

function (ecdf) of the regulatory cycle. Following Born et al. (2020), the ecdf is calculated as

$$F(rc_{t-1}) = \frac{1}{T}\sum_{t=2}^{T} 1_{rc_j < rc_{t-1}} \,, \tag{6.1}$$

with T being the sample size. The term $1_{rc_j<rc_{t-1}} = 1$ if $rc_j < rc_{t-1}$ and 0, else. That is, the transition function equals 1 if the regulatory cycle is at the

Figure 13: Weighted vs. Unweighted cPP (Tight Regime)

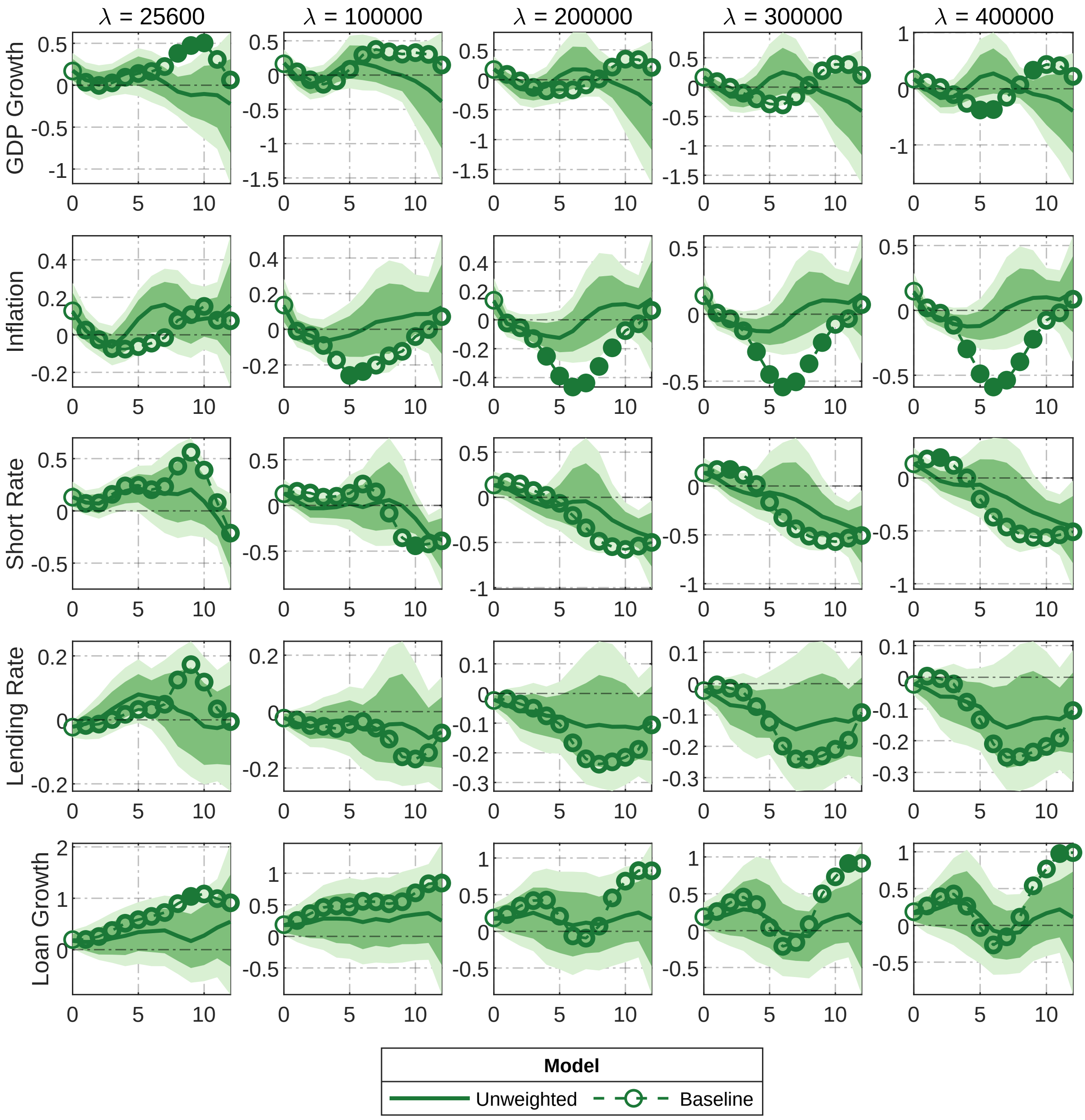


Notes: State-dependent impulse responses to an expansionary loan supply shock in a regulatory tight regime. Solid lines represent median responses from the models with regulatory cycles based on the unweighted cPP-index. Dashed lines depict median responses from the corresponding baseline model. Projection horizons in which the median from the baseline model significantly deviates at the 5% level from the alternative model are shown by shaded circles. Dark (light) areas depict 68% (90%) probability masses.

maximum of the sample. If the regulatory regime is unprecedented loose, on the other hand, $F(rc_{t-1})$ equals 0.

Again, we compute the regulatory cycle applying the one-sided HP-filter with values $\lambda^{RC} = \{25.6, 100, 200, 300, 400\} \times 1,000$ on the GDP-weighted cumulative Prudential Policy-index as the indicator variable rc. As in the baseline case, we use the lagged value of the regulatory cycle.

Figure 14: Weighted vs. Unweighted cPP (Loose Regime)

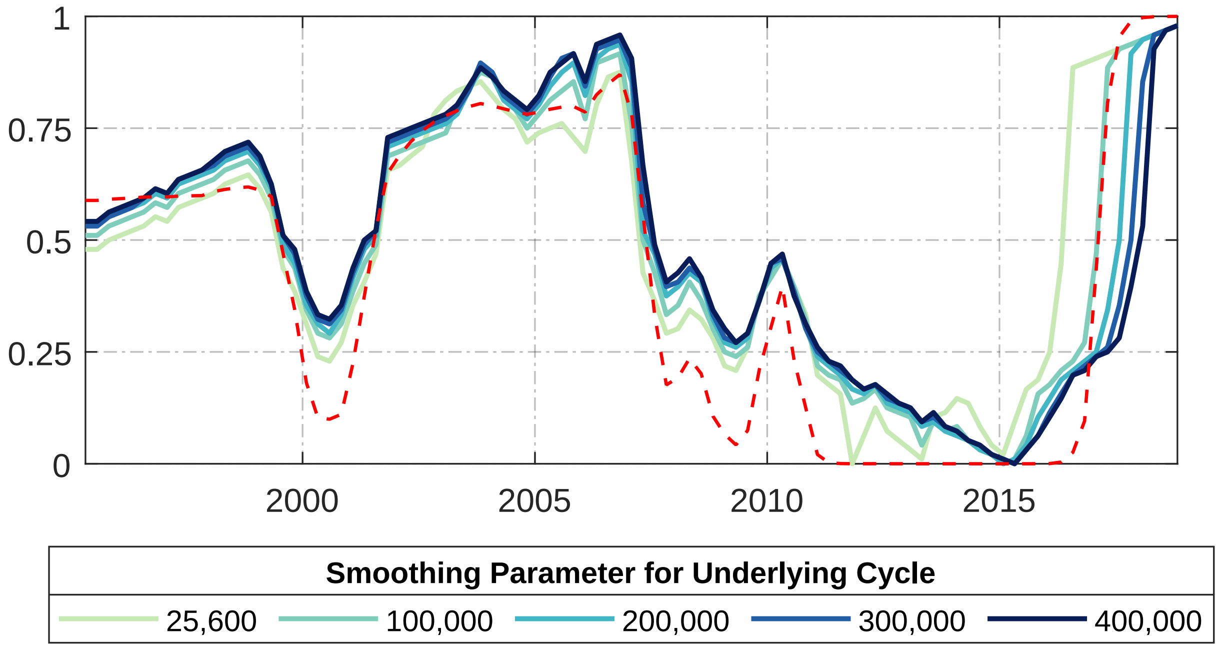


Notes: State-dependent impulse responses to an expansionary loan supply shock in a regulatory loose regime. Solid lines represent median responses from the models with regulatory cycles based on the unweighted cPP-index. Dashed lines depict median responses from the corresponding baseline model. Projection horizons in which the median from the baseline model significantly deviates at the 5% level from the alternative model are shown by shaded circles. Dark (light) areas depict 68% (90%) probability masses.

Figure 15 shows the resulting indicator functions. For comparison, the transition function from the baseline specification with $\lambda^{RC} = 100,000$ is also shown, as these are in the middle of the other transition functions from the baseline model.[29] In principle, both approaches qualify the time periods

[29]We could have used any other transition function, as the correlation between those and the ecdf-based transition functions, for a given λ^{RC}, is a very high 0.97.

Figure 15: Transition Functions from ECDF

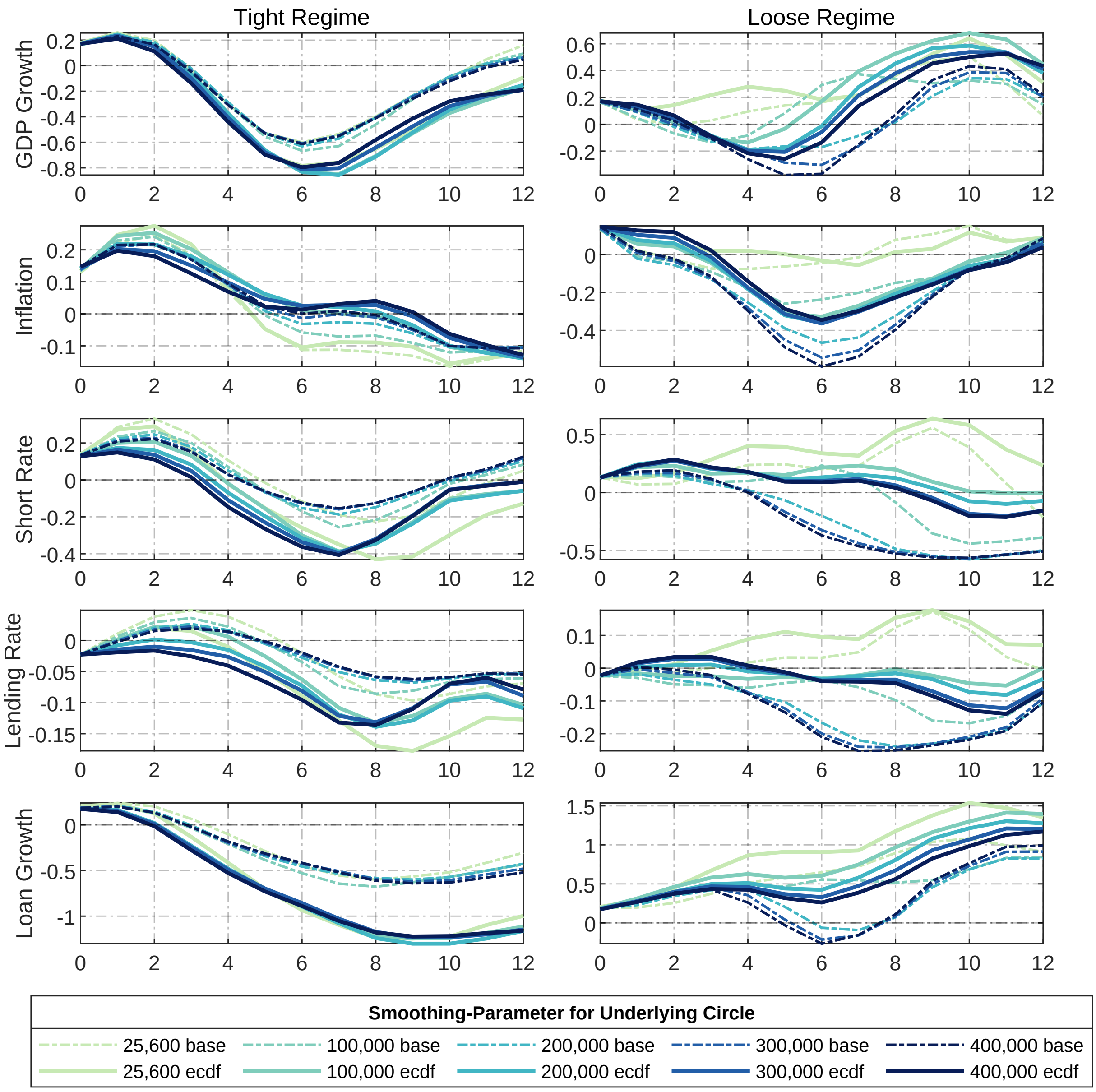


Notes: Transitions functions based on the empirical cumulative density function of the various regulatory cycles. The red dashed line depicts the transition function from the baseline model with $\lambda = 100,000$ for comparison.

of the respective states identically (compare, for example, the course of the dashed line and the light turquoise line belonging to the specification with $\lambda^{RC} = 100,000$). The essential difference lies in the weightings that are attributed to the respective regimes at each point in time. The approach using the ecdf tends to assign relatively higher weights in the loose regime (> 0.5) and lower weights in the tight regime compared to the approach in the baseline specification, as the baseline transition functions is predominantly below the alternatives.

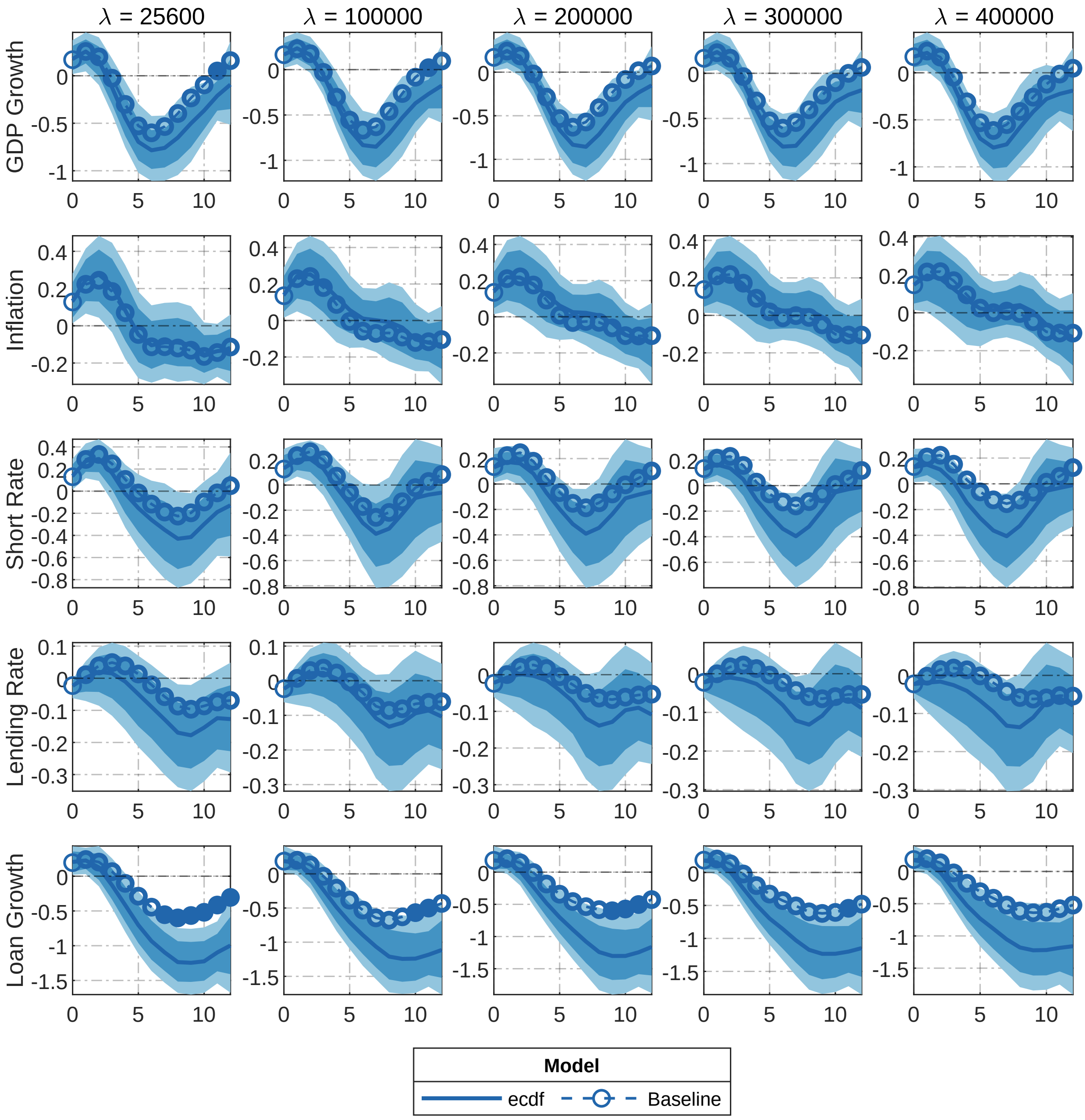
The resulting state-dependent median responses are depicted in Figure 16. In the tight regime, the median responses from our robustness exercise (solid lines) confirm the pattern observed in the baseline models (dashed lines). It is striking that the responses from the alternative specification tend to measure stronger effects of an expansionary loan supply shock. Compared to the baseline specification, output falls by roughly 0.2 percentage points more in the bust phase (-0.6 vs. -0.8). Loan growth even declines twice as much: -1.2 percentage points compared to -0.6 from the baseline model. With the exception of loan growth, the median responses from the baseline model are part of the variation in the alternative models, as illustrated by the unfilled circles in Figure 17. A filled circle highlights that the value of the median impulse response from the baseline model at projection horizon h is outside the 90 percent interval of the alternative specification. For loan growth, the discrepancy in the responses just mentioned becomes apparent. In particular, in specifications where a relatively high frequency is assumed for the regulatory cycle, the median response from the baseline model is in part clearly outside the 90 percent levels of the respective alternative specification.

Figure 16: Comparison of Median Responses



Notes: State-dependent impulse responses to an expansionary loan supply shock. Alternative regulatory regimes are derived from the empirical cumulative density function of the GDP-weighted cumulative Prudential Policy Index. Resulting median impulse responses are depicted by solid lines. Dashed lines report the median responses.

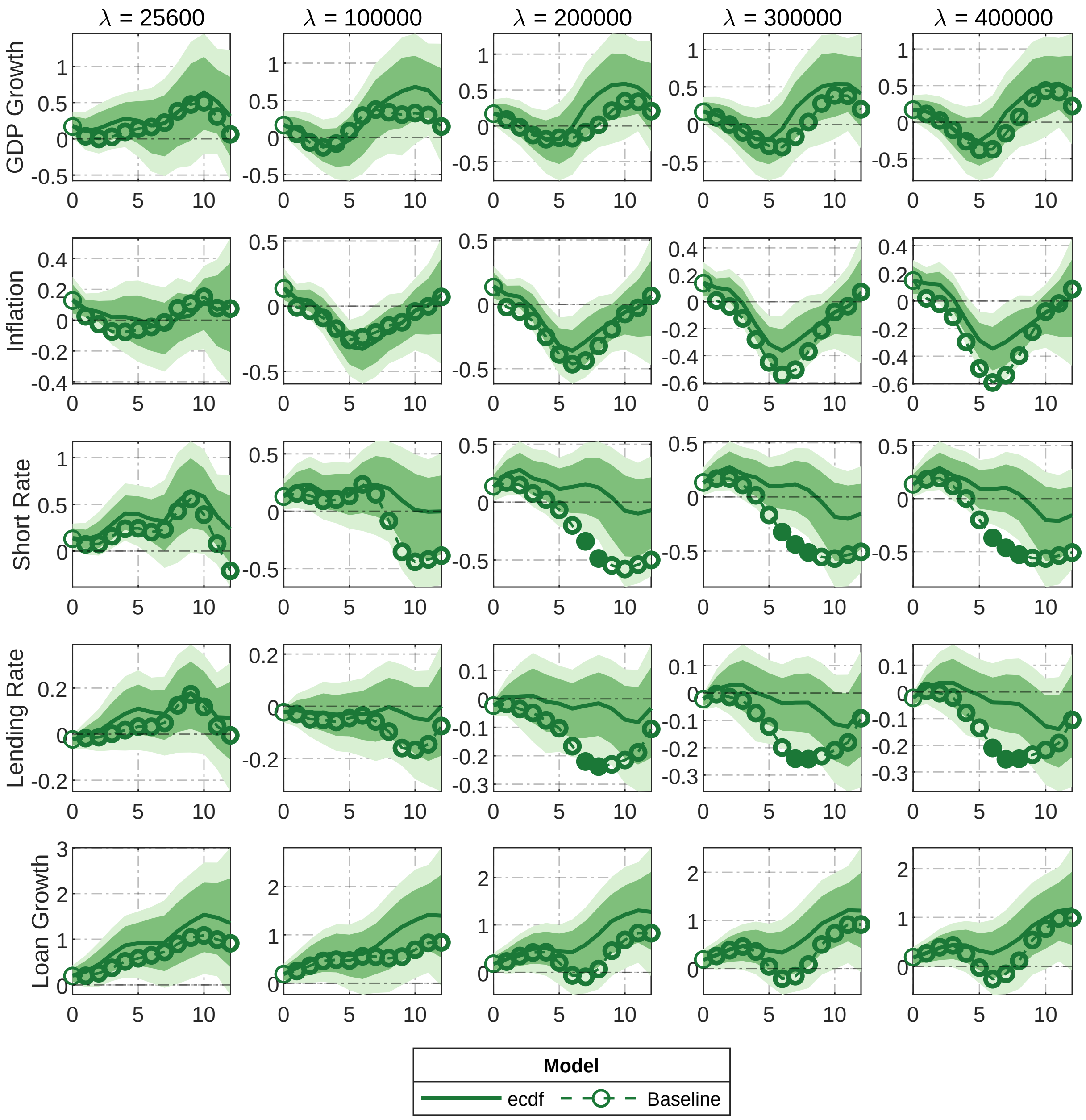
Figure 17: ECDF VS. BASELINE MEDIAN RESPONSE (TIGHT REGIME)



Notes: State-dependent impulse responses to an expansionary loan supply shock in a regulatory tight regime. Solid lines represent median responses from the models with regime determination by means of an empirical cumulative density function. Dashed lines depict median responses from the corresponding baseline model. Projection horizons in which the median from the baseline model significantly deviates at the 5% level from the alternative model are shown by shaded circles. Dark (light) areas depict 68% (90%) probability masses.

The robustness analysis confirms our baseline results for the loose regime in that, in this state, the results are more dependent on the choice of the smoothing parameter λ^{RC}. Again, the patterns of the impulse responses are similar for a given value of λ^{RC}. While the baseline median responses in the tight regime were more at the upper end of the distribution of $\beta_{i,h}^{tight}$ in the alternative specification, as shown in Figure 17, the baseline median responses in the loose regime are more likely to be at the lower end of the distribution of $\beta^{loose}_{i,h}$, as Figure 18 shows. In the case of loans, this means that an expansionary loan supply shock triggers a sustained positive growth of nominal loans in a model with an alternative specification of the transition function. Together with the corresponding responses in the tight regime, we find much more pronounced asymmetric effects here.

Figure 18: ECDF VS. BASELINE MEDIAN RESPONSE (LOOSE REGIME)



Notes: State-dependent impulse responses to an expansionary loan supply shock in a regulatory loose regime. Solid lines represent median responses from the models with regime determination by means of an empirical cumulative density function. Dashed lines depict median responses from the corresponding baseline model. Projection horizons in which the median from the baseline model significantly deviates at the 5% level from the alternative model are shown by shaded circles. Dark (light) areas depict 68% (90%) probability masses.

In principle, this robustness exercise confirms our previous results. Here, too, we find the unclear results in the loose regime. However, there is a potential flaw when using the ecdf. Given our relatively short sample, we cannot rule out the possibility that the ecdf derived from our observations incorrectly represents the true ecdf of the population.

7 Conclusion

Over the past decade or so, credit developments have increasingly become the focus of attention. One key aspect of this is that misguided dynamics harbour great potential to trigger economic turmoil. Analyses of expansive loan supply shocks in particular have intensified, as credit-driven private sector debt has been a key factor in past crises, especially in the euro area.

Prudential measures have proven their worth in counteracting misguided credit developments. This set of instruments has proven to be particularly effective in keeping credit developments on track. Accordingly, this toolbox is being used more and more frequently.

When implementing prudential measures, decision-makers have to resolve a conflict of objectives. If they apply the brakes too hard on expansive credit development, there is a risk that favourable investments will not be made and economic growth will be weakened. On the other hand, if they do not counter such developments vigorously enough, there is a risk that these developments will foster a harmful debt dynamic.

In analysing the role of prudential regulation on economic factors, the empirical literature has so far focused on the effects of the systematic and non-systematic components of prudential measures. We add a further dimension to the existing literature by analysing the role of the regulatory regime for the business cycle effects of expansionary loan supply shocks.

In doing so, we uncover two main results. First, we find that expansionary loan supply shocks in a tight regime cause a noticeable boom-bust cycle. These results hold regardless of the frequency of the chosen regulatory cycle. Comparing the business cycle effects between the regimes, we see asymmetric responses. Loan growth in particular responds noticeably differently. In the tight regime, expansionary loan supply shocks do not sustainably increase credit growth. In contrast, we see that in the loose regime, lending follows a sustained growth path as a result of the shock. However, the responses found in a loose regulatory regime are not as robust. A key reason for this is that it is difficult to identify loose regimes, as prudential measures have so far mainly taken only one form: tighter.

Even if we cannot draw any definite conclusions, the tendencies for asymmetric effects should not be completely ignored in light of the importance of credit development for prudential regulation.

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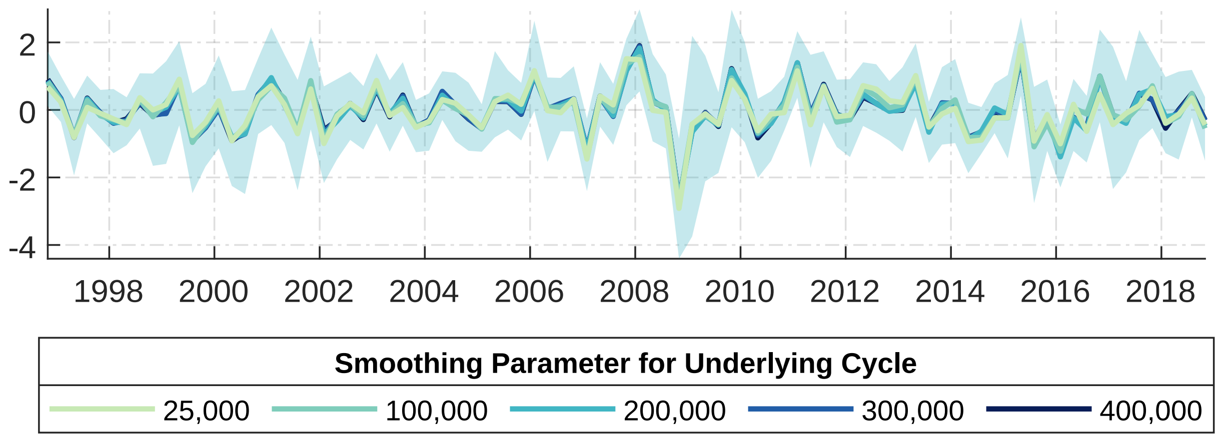
A Identified Shocks

The identified median loan supply shocks are depicted in Figure A.1. The 90% probability band from the model with smoothing parameter value $\lambda^{RC} = 200,000$ is shown for reference. The median shocks are basically indistinguishable, indicating that the shocks are well identified independent from the underlying regulatory cycle. The shocks show noticeable negative oscillations in the first half of 1999, in early 2002, and in the first quarter of 2007, with the negative shock at the end of 2008 being the most obvious. Noticeable positive impacts are identified in the first quarters of 2008 and 2011. The identified shocks can hardly be distinguished from each other, regardless of the choice of the smoothing parameter λ^{RC}.

Figure A.1: Loan Supply Shocks

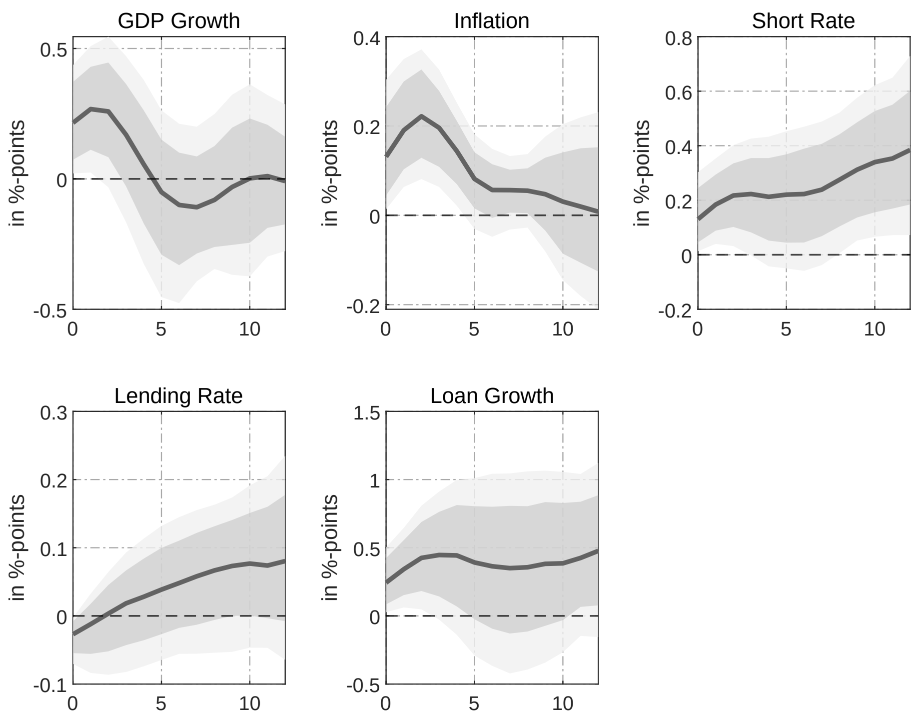


Notes: Solid lines show median shocks. Light area denotes 90 % probability band of the shocks from the model with smoothing parameter $\lambda^{RC} = 200,000$.

B Baseline Linear Model

As far as the linear model is concerned, the responses shown in Figure B.1 match the findings for the euro area in, i.a. Barauskaitė et al. (2022), Mandler and Scharnagl (2020), Altavilla et al. (2019), Gilchrist and Mojon (2018), Gambetti and Musso (2017), or Bijsterbosch and Falagiarda (2015). Concerning the effect on output, loan supply shocks have a notable, yet rather short-lived effect. When the expansionary shock hits the economy, output increases by 0.2 percentage points on impact and peaks at 0.4 percentage points within the first year after the shock hits the economy. Thereafter, the effect gradually decays. Inflation shows a similar but more persistent response. Interest rates follow the rise in inflation. They appear to be more persistent than the developments of inflation. The lending rate initially falls, thereafter permanently reverses to positive rates, which is explained by the development of the short-term interest rate.Finally, an expansionary loan supply shock leads to a sizeable and lasting credit expansion.

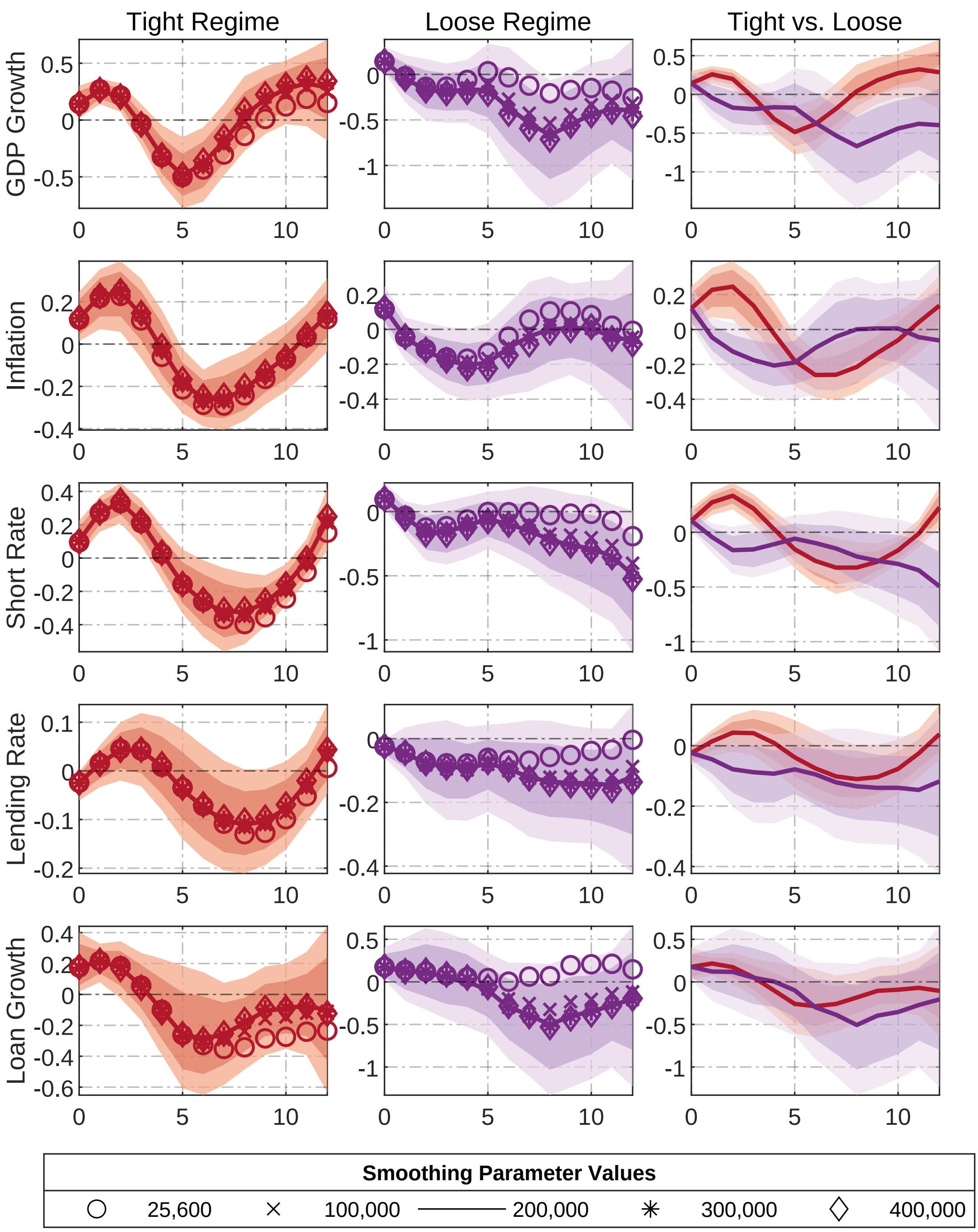
Figure B.1: Linear Model



Notes: Impulse responses to an expansionary loan supply shock from a linear LP model with model specified as described in Section 3. Identifying assumptions are impose on impact. Solid lines depict median responses, accompanied by 68% (dark grey) and 90% probability masses (light grey).

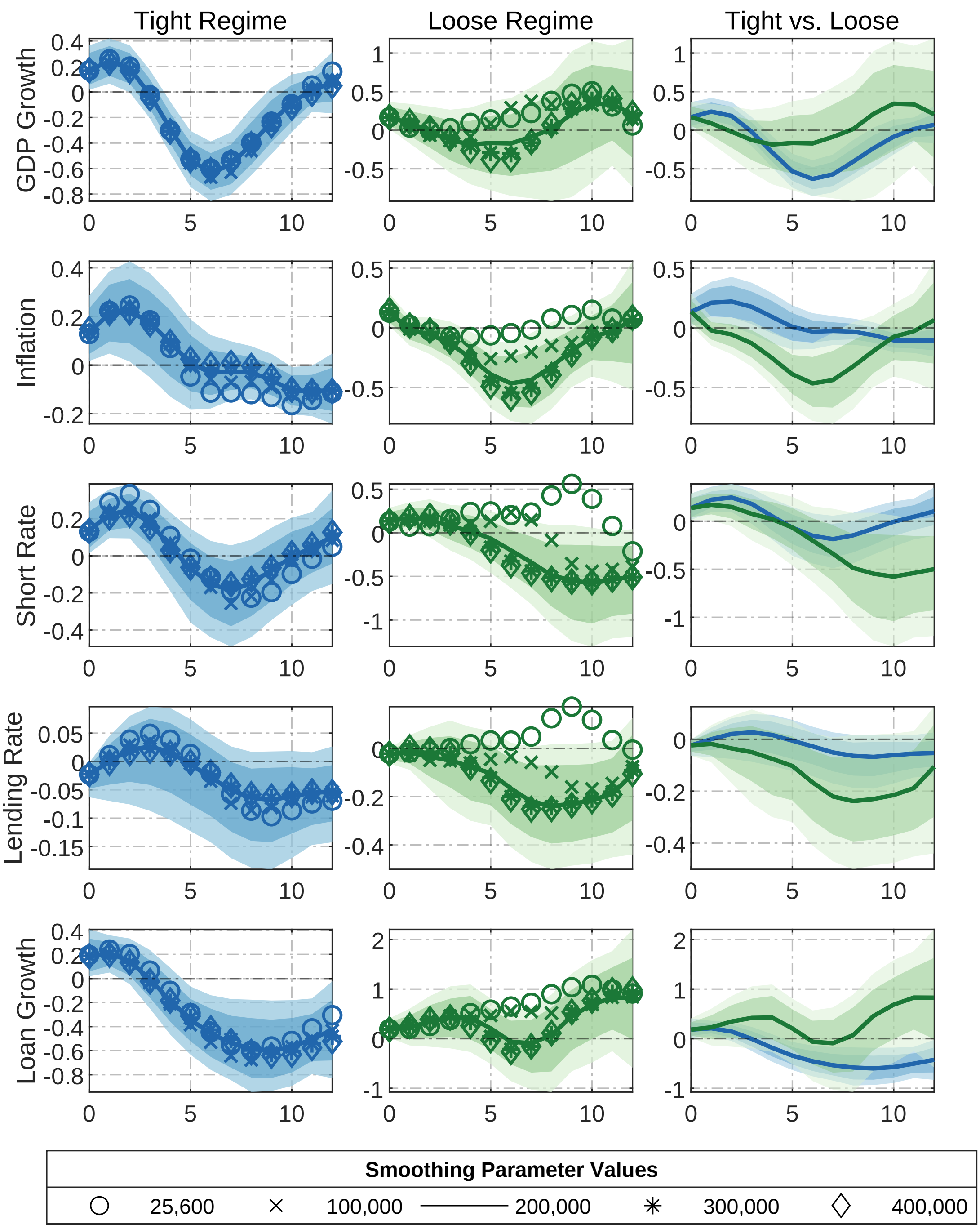
C Supplementary Figures

Figure C.1: Short Sample: Impulse Responses



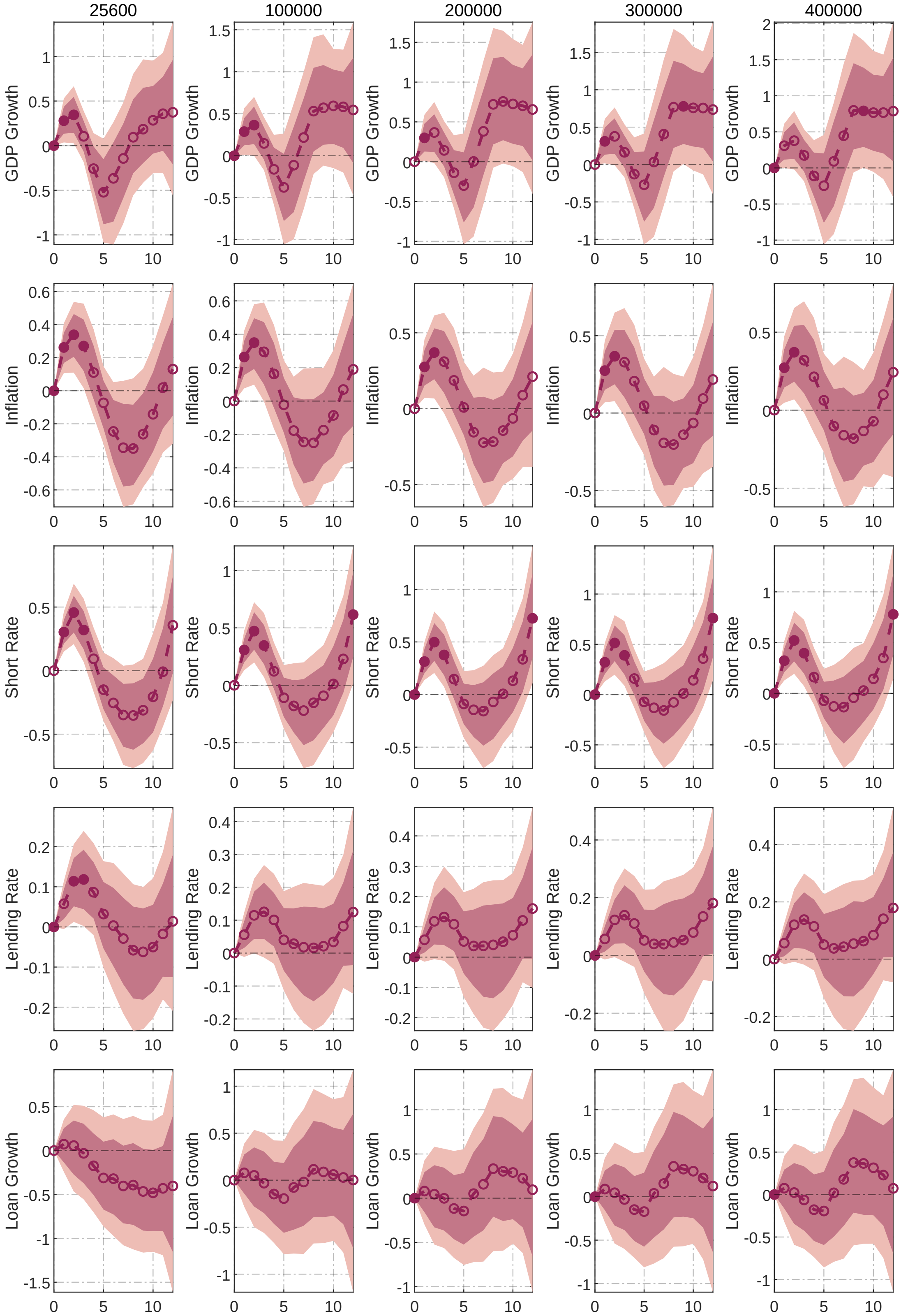
Notes: State-dependent impulse responses to an expansionary loan supply shock in the short sample spanning the period 1995Q1 until 2015Q1. Identifying assumptions are impose on impact. Lines and markers depict median responses in tight (left panel) and loose (center panel) regulatory regimes. Lines and markers depict median responses. For ease of comparison, median responses and probability band from the model with smoothing parameter value 200,000 are shown in the right panel. Smoothing parameter values relate to the smoothing parameter λ^{RC} used in order to extract regulatory cycles, as described in the main text. Dark (light) areas depict corresponding 68% (90%) probability masses.

Figure C.2: Full Sample: Impulse Responses



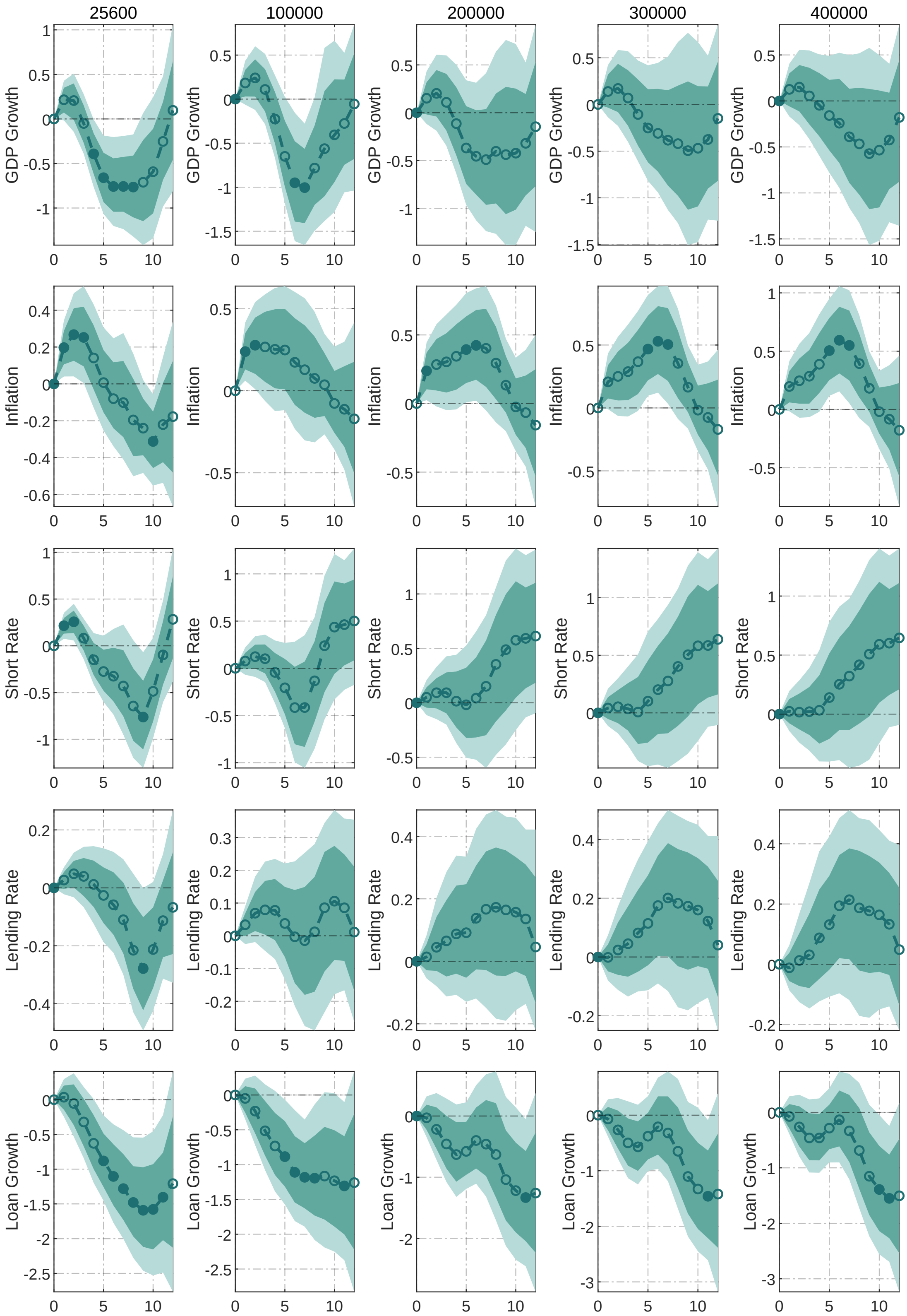
Notes: State-dependent impulse responses to an expansionary loan supply shock in the full sample spanning the period 1995Q1 until 2018Q1. Identifying assumptions are impose on impact. Lines and markers depict median responses in tight (left panel) and loose (center panel) regulatory regimes. Lines and markers depict median responses. For ease of comparison, median responses and probability band from the model with smoothing parameter value 200,000 are shown in the right panel. Smoothing parameter values relate to the smoothing parameter λ^{RC} used in order to extract regulatory cycles, as described in the main text. Dark (light) areas depict corresponding 68% (90%) probability masses.

Figure C.3: Short Sample: Difference in Responses



Notes: Difference between the impulse responses from the tight and loose regime ($\beta_{i,h}^{tight} - \beta_{i,h}^{loose}$) based on the short sample. The dotted lines represent the median responses which are also shown in Figure 5 in the main text. Filled dots indicate projection horizons significant asymmetry at the 5% level. Dark (light) areas depict 68% (90%) probability masses.

Figure C.4: Long Sample: Difference in Responses



Notes: Difference between the impulse responses from the tight and loose regime ($\beta_{i,h}^{tight} - \beta_{i,h}^{loose}$) based on the full sample. The dotted lines represent the median responses which are also shown in Figure 5 in the main text. Filled dots indicate projection horizons with significant asymmetry at the 5% level. Dark (light) areas depict 68% (90%) probability masses.