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Anticipating Credit Developments with Regularization and Shrinkage Methods: Evidence for Turkish Banking Industry

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Abstract

In this paper, we propose the use of regularization and shrinkage methods to address the variable selection problem in predicting credit growth. Using data from the 10 largest Turkish banks and a broader set of macro-financial predictors for the period 2012-2023, we find that the models generated by the Least Absolute Shrinkage and Selection Operator (LASSO) method have superior predictive power (lower level of forecast errors) for bank-level total credit growth compared to alternative factor-augmented models through recursive out-of-sample forecasting exercises. Our baseline findings remain intact against alternative choices of the tuning parameter and LASSO specifications. In addition to the dynamics of the total credit growth, the improvement in prediction accuracy is evident for commercial credit growth at all horizons, while the effect is limited to short-term horizons for consumer credit growth. Furthermore, additional robustness checks show that the baseline results do not vary considerably against different sample coverage and benchmark models. In the subsequent analyses, we utilize the LASSO method to synthesize the "residual credit" indicator as a proxy for excessive credit movements deviating from the level implied by macro-financial dynamics. In the scope of a case study, using this indicator as an input for local projection estimates, we show that recent inflationary pressures have resulted in excessive lending activity, which is not fully explained by macro-financial dynamics, in the period 2020-2023.

Keywords: Credit Growth, Forecasting, LASSO, Residual Credit, Local Projection

JEL Classifications: G21, C53, C55

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Non-Technical Summary

Producing reliable forecasts concerning the path of macro-financial variables has been a key task for researchers and regulators in terms of studying and analyzing financial stability. Among other indicators, credit growth assumes substantial importance in assessing risks to financial stability, particularly in emerging economies with heavier reliance on the banking sector to facilitate the flow of funds from net savers to net borrowers. Excessively high credit growth tends to accommodate asset bubbles and exacerbate indebtedness of economic units. The asset bubbles are likely to burst in the subsequent downturn of the economic cycle, leading to financial crises. On the other hand, very low credit growth serves as a signal of acute financial constraints, potentially diminishing consumption and investment as well as causing lower potential growth and productivity (in the long-term).

In this context, it is essential to improve modeling practices in forecasting credit growth and anticipating the level of credit extension implied by (or in line with) macro-financial conditions. However, similar to other macro-financial variables, predicting credit growth is also plagued with the dimensionality problem due to the existence of a potentially long list of predictors. Adopting populated models may be useful to reduce the bias of estimation and forecasts, but is also likely to induce heightened variability.

In this paper, we propose the use of the Least Absolute Shrinkage and Selection Operator (LASSO) technique to form linear models when predicting the bank-level credit growth rates in the Turkish banking industry. Utilizing a wide set of macro-financial covariates and bank-level data from the 10 largest Turkish banks, we evaluate the predictive power of LASSO-based models against factor-augmented predictive models. Our expanding window forecasting exercises show that the LASSO method produces linear specifications with a lower level of forecast errors to analyze total and commercial credit growth, whereas the same level of improvement is not observed for consumer credit growth. Our findings are invariant to a range of robustness checks.

In the later part of this study, again by employing the LASSO method, we quantify the degree of divergence between realized credit growth and the level implied by macro-financial conditions at bank level, namely residual credit. To operationalize this informative measure, we undertake a case study to shed more light on the implications of inflation shocks on financial stability. Our subsequent local projection estimations show that inflationary pressures are related to the excess credit extension monitored through higher values of residual credit proxy.

The findings of this paper are useful from the perspective of regulators and policymakers. The modeling approach supported by the LASSO technique can yield linear specifications to forecast bank-level credit growth under varied scenarios. It is also helpful to monitor the excess credit growth that deviates from the level implied by the current macro-financial outlook. More importantly, the procedure can be preferred to form satellite models to be integrated into stress testing frameworks.

I. Introduction and Related Literature

A precise anticipation of the future course of macro-financial variables matters to policymakers and financial market practitioners for better monitoring the macroeconomic outlook, ensuring financial stability, assessing the effectiveness of the monetary policy transmission mechanism and constructing superior trading and hedging strategies (Bernanke et al., 2005; Bai and Ng, 2008; Günay, 2018). In this regard, regulatory attention to abnormal credit developments is justified on multiple grounds. Credit growth that persistently exceeds economic growth is considered a cardinal early warning indicator for banking crises (Drehmann, 2013; Giese et al., 2014; Alessandri et al., 2022). In order to avoid the drastic consequences of recessions following financial instability (Jordà et al., 2011), in addition to indicators such as house price growth and debt servicing capacity, policymakers emphasize the monitoring of the degree of deviation between credit growth and macroeconomic fundamentals, even classifying it as an input for the design and execution of macroprudential policies (Drehmann and Juselius, 2014).[5]

Given the relatively underdeveloped capital and debt markets in emerging countries, the path of bank credit is particularly important for economic agents in such economies that rely more heavily on bank-based financial intermediation. Unusually low credit growth in such environments may indicate aggravated financial constraints, leading to declining productivity (Beck et al., 2006; De Sousa and Ottaviano, 2018), while rapid credit expansions may temper indebtedness and current account balance without improving long-term income (Büyükkarabacak and Valev, 2010; Unger, 2017).

Forecasting credit growth is also important for regulators and economists in emerging markets, as it serves as an integral component of stress-testing procedures. Traditional stress test designs available to central bankers and bank supervisors employ satellite models to transmit macroeconomic shocks to banking sector outcomes and balance sheet dynamics (Foglia, 2009; Henry et al., 2013). This requires explaining credit growth realizations with appropriate model specifications, and consequently, determining a variable selection process to reveal which specific macro-financial series are most informative in explaining credit growth trajectories, ultimately to evaluate how banks' risk and capital adequacy stand under adverse shocks, especially in the post-crisis era (Onder et al., 2016; Schuermann, 2020).

Nevertheless, in line with the limitations of modelling other macro-financial indicators such as inflation and economic growth, the assessment of credit growth is also subject to an empirical problem, which is defined as the bias-variance trade-off (Clark and McCracken, 2009; Belkin et al., 2019). Due to the accessibility of numerous explanatory variables, this issue is at the core of the model selection dilemma given that a broader coverage of predictors may reduce the prediction bias but leads to increased variability. Relatedly, less parsimonious

[5] The Basel Committee on Banking Supervision (BCBS) recommended the activation of a countercyclical capital buffer based on the cyclical movements in the credit-to-GDP ratio.

models produce less accurate out-of-sample forecasts. In this study, we propose a remedy to this problem in anticipating credit growth by drawing on the methodological aspect of regularized regression using the Least Absolute Shrinkage and Selection Operator (LASSO) technique, especially in the context of a large emerging market, Türkiye, which is characterized by a higher financial deepening through bank lending activities. Moreover, we also argue that the implementation of LASSO for model selection can be an alternative approach to quantify the degree of separation between actual credit growth and the level implied by the macro-financial outlook, thereby providing useful early warning information for policymakers and regulators.

In this paper, we primarily assess the credit growth in the Turkish banking industry by using the shrinkage method of LASSO for variable selection and accompanying forecasting modules. We exploit data from the 10 largest Turkish banks and a wide set of potential bank-level and macro-financial predictors (125 series). Our sample period covers between January 2012 and June 2023. By way of preview, our baseline results from recursive pseudo out-of-sample forecasting exercises show that the LASSO model considerably outperforms the benchmark factor-augmented model. The improvement in the forecasting accuracy is evident in the form of lower root mean squared prediction errors (RMSE) values and hence positive out-of-sample R-squared proxies which show improvements of almost 50-60% for total credit growth across all horizons. Similar improvements are observed for commercial credit growth, but only over short-term horizons for consumer credit growth. Moreover, we document that baseline findings remain intact when we use different approaches to determine the tuning parameter and when we utilize different constraints to define the LASSO optimization procedure. Our results do not vary significantly with robustness checks involving alternative sample coverage, estimation intervals and benchmark models. We also apply LASSO variable selection to forecast a variety of commercial and consumer credit sub-components ranging from small and medium-sized enterprise (SME) loans to large-firm loans, and from general-purpose to vehicle segments.

On top of forecasting exercises, we take advantage of the LASSO variable selection to define "residual credit" (the difference between the predicted value of credit growth and the realized values for a recent examination window), which is a synthetic indicator proxying for how the actual credit growth differs from the level suggested by macro-financial dynamics. To demonstrate how such a proxy for excess credit movements can be used as an input for additional econometric analysis involving questions about financial stability, we undertake a simple case study. To this end, we investigate the dynamic relationship between residual credit and inflationary pressures for the period from January 2020 to June 2023 by using the local projection method of Jordà (2005). Our results indicate that inflationary shocks have a positive and significant effect on residual credit in the short and medium run with a subsequent reversal in the long run.

This study attempts to contribute to two strands of the literature. First, we add to the prior works that focus on evaluating the use of the LASSO method for the variable selection of macroeconomic and financial phenomena. Model selection and shrinkage techniques have been applied in various fields including financial markets. As an example, portfolio optimization and asset allocation problems in the area of finance require the estimation of the variance-covariance matrix of asset returns. LASSO-type constraints can be imposed to obtain optimal solutions in the presence of highly collinear returns of financial assets (Brodie et al., 2008; Fan et al., 2012). The LASSO model is also found to be useful in calibrating the existing forecasting models of financial asset volatility based on autoregressive schemes, and in choosing the parsimonious lag structure in particular (Ding et al., 2021). Barokas (2022) uses the LASSO estimator to predict the credit default swap (CDS) risk premium of BRICS (Brazil, Russia, China, South Africa) and MINT (Mexico, Indonesia and Türkiye) countries. On the other hand, Perdeiy (2015) focuses on employing unconventional financial indicators as covariates in LASSO regression.[6] In addition, some studies such as Sermpinis et al. (2018) and Nazemi and Fabozzi (2018) assess the usefulness of the LASSO technique for predicting credit risk.[7]

In a data-rich environment with an increasing number of potential predictors, forecasting macroeconomic variables also requires gathering the necessary information in an efficient and simple way. Li and Chen (2014) combine LASSO-type models with widely used dynamic factor models and demonstrate an increasing predictive ability for a group of macroeconomic variables such as industrial production, consumer prices, durable consumption and hourly earnings. Kreiner and Duca (2020) use the LASSO approach to forecast the unemployment rate, while Kundan (2023) investigates the determinants of house prices with the LASSO method. Such studies are not limited to aggregate macroeconomic variables but are also extended to firm-level analysis. McKenzie and Sansone (2017), Miyakawa et al. (2017), and Coad and Srhoj (2020) utilize LASSO regression to predict firm-level growth and performance.[8]

Last but not least, another part of this literature has been developed to apply the LASSO technique to empirical questions arising from the banking industry, especially in the context of stress-testing practices. Chan-Lau (2017) employs LASSO regressions in the model selection stage of stress testing as well as in asset-quality forecasting. Kapinos and Mitnik (2015) argue that the LASSO technique can relate macroeconomic variables to bank performance-related indicators. Kupiec (2018) argues that LASSO-type models can be a viable alternative for calibrating stress-testing processes. We aim to further this strand of literature by implementing LASSO variable selection to generate more accurate forecasts of bank-level

[6] Moving from financial markets to the context of commodity trading markets, Zhang et al. (2019) argue that shrinkage methods can provide a source of predictability for oil-price returns in the face of a large set of predictors by outperforming a number of competing models.

[7] Sermpinis et al. (2018) investigate the determinants of market-implied credit ratings in relation to financial factors, market-driven indicators and macroeconomic predictors. Nazemi and Fabozzi (2018) study the relationship between recovery rates of U.S. corporate bonds and macroeconomic variables that are selected by LASSO.

[8] Tian et al. (2015) investigate the relative importance of various bankruptcy predictors commonly used in the existing literature by implementing the LASSO procedure.

credit growth in an emerging market environment, which is characterized by a dominant role of conventional banks in financial intermediation.

Second, the existing empirical literature on monitoring and forecasting credit dynamics in the Turkish setting is rather nascent. Part of this literature faces the problem of identifying abnormal credit movements. Güney et al. (2018) employ univariate unobserved component models to capture cyclical movements in total, commercial and consumer credit growth by emphasizing their superior forecasting performance compared to autoregressive models. Çolak et al. (2019) identify the moderate to excessive credit expansion/contraction phases through credit gap indicators by using a variety of filtering and credit ratio choices. Furthermore, they document that factor analysis, which summarizes a broad set of local and global macro-financial indicators, has an incremental improvement in forecasting excessive credit movements over baseline autoregressive models.

Another part of this literature aims at mapping the dynamic interactions between credit and business cycles. Çepni et al. (2020) integrate wavelet coherence analysis to track the co-movements between the extent of financial intermediation and the level of economic activity, with a special interest in the decomposition in terms of denomination currency, borrower type, lender type and the disaggregation of economic growth (in terms of consumption vs. investment growth). Çolak et al. (2020) investigate the time-varying degree of coherence between credit and business cycles by calculating synchronization, concordance and similarity indices. Additionally, they decipher the role of local financial conditions, macroeconomic volatilities, and capital flows in explaining cyclical coherence through Tobit regressions. We try to advance these strands of the literature on Turkish credit markets by introducing the shrinkage technique into the variable selection process of predicting credit growth through LASSO-class models.

The remainder of the paper is organized as follows. Section II provides the details of the sample coverage and data sources for the bank-level and macro-level variables. Section III outlines the methodological aspect of this study along with a general description of LASSO variable selection technique. Section IV presents the main empirical findings, additional analyses and robustness checks. Section V concludes the paper and discusses potential policy implications.

II. Data

For this study, we use confidential balance sheet and income statement data from Turkish commercial banks, which we access through monthly regulatory filings available via the Central Bank of the Republic of Türkiye (CBRT). Our panel sample straddles the period from January 2012 through June 2023. The set of sample banks is restricted to the 10 largest state-owned, private, and foreign banks to avoid the effect of outliers by excluding smaller private banks as well as the local branches of foreign banks. We also omit participation and development banks because their business plans, customer bases, branch networks, loan pricing, and lending motives tend to differ from those of their commercial counterparts. The sample represents the majority of financial intermediation activity in Türkiye as the selected banks extend 89.5%, 87.7% and 95.2% of total, commercial, and consumer outstanding loans, respectively, as of June 2023.

In addition to total loan growth rates (considered as the outcome variable) and other bank-level characteristics (considered as potential covariates), we compile a broad set of bank-invariant macroeconomic and financial variables from a variety of sources including the CBRT, the Turkish Statistical Institute (TurkStat), the Ministry of Treasury and Finance, and Bloomberg. The topics of interest for the aforementioned variables cover a wide set of areas, ranging from financial markets, economic growth and fiscal policy to labor markets, current account dynamics and structural characteristics of the banking sector. The final pool of donors for the variable selection process and forecasting exercises is presented in the Table A1 of the Appendix. All variables have been subjected to the necessary transformation.

III. Methodology

An important problem facing empirical researchers is the so-called bias-variance trade-off. It is known that the prediction error of any empirical model can be decomposed into the terms of total noise level (which cannot be eliminated), squared bias (resulting from the incorrect assumptions of the underlying method), and the variance of the predictor (caused by the sensitivity of the method to the noise in the calibration data) (Chan-Lau et al., 2017; Ahrens et al., 2020). There is a greater chance of reducing bias when the model is flexible and complex, and includes an extensive number of potential covariates. However, populated models are also likely to suffer from poor out-of-sample forecasting performance due to a higher degree of variability, especially for low-frequency economic variables. In this context, regularization methods are able to improve prediction accuracy by penalizing model complexity, avoiding over-fitting and performing variable selection and parameter estimation simultaneously.

Originally introduced by Tibshirani (1996) as a regularized extension of conventional linear regression, LASSO has been placed among the other machine-learning techniques. The underlying assumption of this technique is the approximate sparsity condition, which states that a comparatively small set of all potential predictors is actually relevant (Belloni et al., 2014). While least squares estimation is governed by an unconstrained minimization problem, LASSO augments this approach by imposing a convex but non-smooth L-1 constraint. In other words, it enforces a penalty term on the parameter coefficients, while simultaneously minimizing the sum of squared errors of the model (Kupiec, 2018; Ding et al., 2021). The general representation of the optimization problem under the LASSO method for the estimation is demonstrated below. The general model of interest is as follows:

$$y_i = X_i'\beta + \varepsilon_i \tag{1}$$

where y denotes the outcome variable, X represents the set of regressors, i stands for cross-sectional units (in our case banks), β is the corresponding coefficient vector and ε is the stochastic error term. LASSO can be stated as a solution to the following minimization problem for p number of regressors and n number of observations:

$$\frac{1}{n}\sum_{i=1}^{n}(y_i - X_i'\beta)^2 + \lambda\sum_{j=1}^{p}|\beta_j| \tag{2}$$

where λ is a tuning parameter controlling the extent and type of penalization through the absolute size of the coefficients, while j refers to the individual members of potential covariate list. If λ is set to zero, the LASSO estimation is reduced to conventional Ordinary Least Squares (OLS) estimation, whereas increasing λ values correspond to the cases where more coefficients are shrunk to zero and consequently excluded from the model due to the signal that the related variable has no predictive value. A variety of methods are available to determine the roughness parameter. In the baseline case of this study, we allow the λ parameter to be determined by Extended Bayesian Information Criteria (EBIC), but we also show that our results are invariant to alternative ways of choosing the aforementioned parameter in the context of robustness tests.

Recent developments in the statistics literature show the increasing role of penalized approaches to improve modeling practices (Zou, 2006). In particular, LASSO has a wide range of applications due to its advantages (Belloni et al., 2014; Nazemi and Fabozzi, 2018; Sermpinis et al., 2018; Ahrens et al., 2020). First and foremost, LASSO can assess the relative importance of independent variables in explaining a given dependent variable and can provide sparse solutions to the model selection problem when dealing with multicollinearity thanks to its low variance compared to the OLS estimator. Therefore, it provides more stable and parsimonious models (Zou, 2006; Zou et al., 2007). Second, LASSO can improve the out-of-sample predictive power of the empirical models. Third, LASSO is computationally efficient to deal with high-dimensional data together with a path-wise coordinate descent algorithm, which provides a means for faster estimation (Hastie et al., 2009). Fourth, the implementation of LASSO is also appropriate for policy impact evaluation and causal inference, for instance, when selecting controls to address omitted variable problems and selecting instruments to alleviate endogeneity problems.

As emphasized by Fan and Li (2001), Zou and Hastie (2005) and others, the subset of variables and estimated coefficients selected by LASSO-based regressions might vary dramatically over time with temporary shocks and the revision of the estimation sample period. This phenomenon is quite common in the forecasting discipline (De Mol et al., 2008). To overcome this problem in assessing the predictive performance of the LASSO variable selection process, we adopt a recursive pseudo out-of-sample forecasting exercise strategy with an expanding window setting. In the first step, we implement LASSO to predict bank-level credit growth using the panel data of Turkish banks for the period from January 2012 to December 2019. Then, we obtain out-of-sample forecasts for the horizon $h = 1, \dots, 12$ ranging from 1-month (January 2020) to 12-month-ahead (December 2020). These forecasts are then compared with bank-level credit growth realizations for each forecast horizon. Forecast performance is quantified in terms of RMSE. In the second step, we extend the estimation interval by one step (January 2012-January 2020) and then run a forecasting exercise for the same forecast horizon to extract errors. In the later stages, this iterative process is repeated until the end of the entire sample period.

A true assessment of forecasting accuracy also requires a comparison with a benchmark model. For the sake of empirical analysis, we choose the widely used static factor approach for the comparison. To this end, we apply Principal Component Analysis (PCA) to derive static factors of contemporaneous and lagged classes of covariates, separately. The PCA technique summarizes the driving forces of a high-dimensional data set with a small number of orthogonal components, for which the first principal component explains the highest proportion of the total variation. Facing the dimensionality problem, the existing literature highlights the practicality of factor-augmented predictive models in explaining the course of macroeconomic variables (Bernanke et al., 2005; Mumtaz and Surico, 2009). Studies such as Li and Chen (2014), Kapinos and Mitnik (2016), Zhang et al. (2019), and Kreiner and Duca (2020) also favor static and dynamic factor models as benchmark specifications to contrast with the LASSO variable selection process.

We form factor-augmented regressions to predict credit growth by using two factors taken as the first principal component of the level and lagged values of the main regressor set. Similar to LASSO, this analysis is also performed in a recursive fashion to mitigate stability concerns and look-ahead bias. As the final product of the forecast comparison, by following Zhang et al. (2019), we use aggregated RMSE values to synthesize an indicator that summarizes the degree of forecast accuracy gains achieved by using LASSO variable selection over the competing factor-augmented method. Originally proposed by Campbell and Thompson (2008), we use out-of-sample R-squared to evaluate the out-of-sample predictive accuracy of the LASSO model relative to the benchmark of the factor-augmented model as follows:

$$R_{OS}^2 = 1 - \frac{RMSE_{LASSO}}{RMSE_{PCA}} \tag{3}$$

Where R_{OS}^2 represents out-of-sample R-squared, $RMSE_{LASSO}$ and $RMSE_{PCA}$ denote the aggregated RMSE of predictive models created using LASSO variable selection and PCA dimensionality reduction methods, respectively. The observations of positive R_{OS}^2 values ascertain that the examined model yields more reliable forecasts than those of benchmark model in terms of the proportional reduction in the deviations of forecasts from actual credit growth tendencies.

IV. Empirical Results

In this section, we present a comprehensive set of main and complementary empirical findings. First, we provide the baseline exercise results to demonstrate the improvement in forecasting accuracy thanks to the use of the LASSO technique in variable selection over the alternative modeling technique of factor-augmented regressions to analyze total, commercial, and consumer credit growth rates. Second, we implement additional analyses by using alternative ways to determine the tuning parameter and alternative LASSO methods. The third step entails the robustness checks using different assumptions such as estimation periods and bank coverage along with alternative benchmark model choices to perform forecast evaluation. In the next stage, we extend our investigation to the sub-components of commercial and consumer credits ranging from SME to large corporate loans and from general-purpose to housing loans. The final stage of our empirical setting involves the use of the LASSO variable selection process to track excessive credit movements and how it can be employed as a policy toolkit, particularly by using the specific case of the interaction between abnormal credit movements and inflationary pressures through the local projection method.

IV.I. Baseline Findings with LASSO Method

As described earlier, our main analysis comprises recursive forecasting exercises in line with the expanding window strategy. Figure 1 illustrates the first step of this procedure for the total credit growth of a randomly selected Bank ABC (with a masked bank identifier). To begin with, the selection of variables spanning the period January 2012-December 2019 is performed by considering bank characteristics (with a panel data structure) and the macro-financial data set, and guided by conventional LASSO estimation with a tuning parameter chosen by EBIC. Then, a selected subset of predictors is utilized to generate forecasts (for Bank ABC) up to a 12-month horizon.

Figure 1 demonstrates how the forecasts can be contrasted with the actual credit growth realizations. The beginning of the forecast period (from January 2020 onwards) is also appropriate to scrutinize the predictive ability of the LASSO selection method since, during this period, the outbreak of Covid-19 caused job losses as well as pressure on household and corporate earnings that necessitated a phase of monetary and fiscal expansion resulting in a credit growth that deviated from the level implied by banking dynamics and the macroeconomic conjuncture. Such an outlook culminated in a consensus in which the existing macroeconometric models had difficulty in forecasting macro-financial target variables such as inflation, economic growth and, more relevant to our case, credit growth. Besides, the subsequent shocks such as the geopolitical tensions surrounding the Russia-Ukraine War (and the related spike in global energy prices), provide the necessary uncertainty in the financial stability outlook during this period to truly test the predictive ability of the competing methodologies. The aforementioned forecasts are made for all the sample banks, similar to Bank ABC. After the first round of forecasting, we go back to the first step and expand the in-sample estimation interval by adding one more month (January 2012-January 2020 instead of January 2012-December 2019) and repeat the analysis. This approach is followed until the end of the sample period (June 2023) to accumulate a full set of credit growth forecast errors and the resulting RMSE values. After evaluating the LASSO method, the same estimation strategy is also duplicated with a factor-augmented model.

Table 1 shows the improvement in prediction performance of the LASSO model, relative to the factor-augmented models using out-of-sample R-squared indicators for all forecast horizons. The top panel indicates that the LASSO technique outperforms the benchmark model in forecasting total credit growth. The success of the LASSO model is evident in the positive out-of-sample R-squared balances, which reflect an improvement of about 60% in terms of forecasting accuracy. The superiority over the benchmark model is maintained across different forecast horizons, highlighting the ability of the LASSO model to perform (both) short- and long-term forecasting tasks. The middle panel of Table 1 iterates the exact same exercise for one of the two main components of total credit: TL commercial credits.[9] The LASSO variable selection outperforms the benchmark for both short- and long-term horizons, albeit with a smaller improvement in prediction accuracy compared to total credit growth. We complement this analysis by focusing on the second important component of total credit, namely credits to households for specific purposes.[10] Here, the results are mixed in the sense that LASSO still outperforms the benchmark specification for the short-term forecasting horizon, while such an improvement is not evident for the medium- and long-term forecasting of consumer credit growth.

Considering the recent data and dynamics, the LASSO variable-selection process yields valuable insights about the relevance of individual data series (from different categories and observation levels) to total bank-level credit growth. In this context, we observe that a variety of macro-level variables are informative such as industrial production, industrial revenue indices, capacity utilization ratio, current account balance and employment. Similarly, a large number of variables pertaining the local financial conditions and markets emerge as relevant indicators such as CDS, implied volatility, and M3 money supply. In terms of bank-level characteristics, the series describing funding, liquidity, credit risk and profitability are found as important proxies. When we turn our attention to variables closely following the outlook of commercial credit growth, apart from the aforementioned variables, we see that public finance, employment and capital flow variables are regarded as significant, whereas additional dimensions of financial conditions via VIX index, currency developments and dollarization ratio also play a significant role. In predicting commercial loan growth, bank-level indicators of loan

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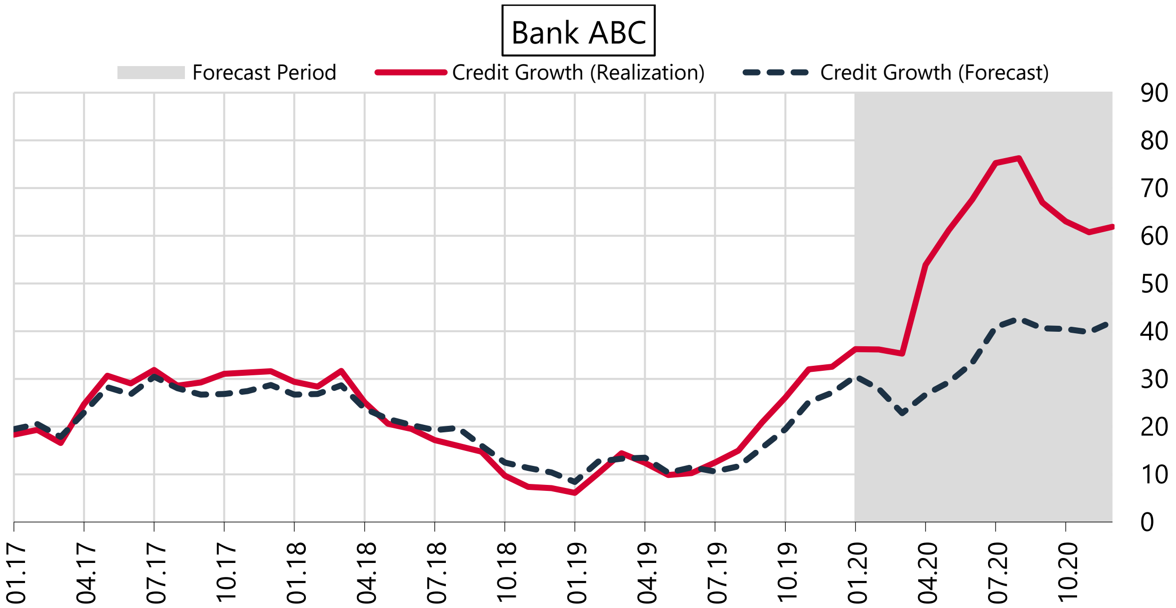
[9] We exclude the FX-denominated loans from the forecast analysis because FX loan growth is mechanically driven by the exchange rate movements, is heavily regulated and does not truly reflect the underlying deepening of financial intermediation activities.
[10] Consumer loan segment includes individual credit cards and overdraft accounts.

interest rates and capital adequacy ratio are further determined as variables with superior informative value.

Figure 1: General Representation of Prediction Procedure



Notes: This figure demonstrates the initial step of the recursive pseudo-out-of-sample forecasting exercise for a randomly selected bank. The in-sample estimation period (light area) for LASSO variable selection is designated as January 2012-December 2019, while the out-of-sample forecasting period (shaded dark area) is taken as January 2020-December 2020. The solid red line represents annual credit growth rate realizations of Bank ABC, while the blue dashed line represents in-sample predictions and out-of-sample forecasts for the annual credit growth rate.

Table 1: Out-of-Sample Predictive Accuracy

Total TL Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.620	0.591	0.573	0.571
	h=5	**h=6**	**h=7**	**h=8**
	0.578	0.582	0.586	0.595
	h=9	**h=10**	**h=11**	**h=12**
	0.613	0.613	0.615	0.622
Commercial TL Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.555	0.512	0.480	0.476
	h=5	**h=6**	**h=7**	**h=8**
	0.500	0.522	0.517	0.491
	h=9	**h=10**	**h=11**	**h=12**
	0.471	0.453	0.417	0.386
Consumer Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.464	0.346	0.211	0.080
	h=5	**h=6**	**h=7**	**h=8**
	-0.013	-0.121	-0.224	-0.305
	h=9	**h=10**	**h=11**	**h=12**
	-0.364	-0.406	-0.403	-0.397

Notes: This table reports the forecast accuracy via out-of-sample R-squared values (of LASSO model relative to benchmark factor-augmented model) which are obtained from recursive pseudo-out-of-sample forecasting exercises. The sample comprises 10 large banks operating in the Turkish banking industry. The initial in-sample estimation period for LASSO variable selection is designated as January 2012-December 2019, while the initial out-of-sample forecasting period is taken as January 2020-December 2020. Recursive iterations are performed by expanding the in-sample estimation interval by one-month increments in each step until the end of whole sample period. Top, middle and bottom panels demonstrate forecasting performance for total TL, commercial TL and consumer credit growth, respectively. Forecast improvements are evaluated for h=1,...,12 horizons.

IV.II. Alternative Ways to Select Tuning Parameter and Alternative LASSO Specifications

Having established that the LASSO model is likely to offer advantages for anticipating credit growth tendencies, in the next step, we try to show that our baseline results are not driven by the parameters and methodological aspects of the LASSO technique. Within this framework, the first aspect at the researcher's discretion is how to set the tuning parameter that governs the extent of the penalty for model sparsity. As emphasized earlier, our main results are obtained by letting the tuning parameter (λ) be defined by the data and information criteria via EBIC. As can be seen in Table 2, when we follow Akaike Information Criterion (AIC), the results do not vary considerably, as the LASSO model is useful in proportion to the benchmark model for total and commercial credit growth at all horizons, while such an improvement is only applicable to the short-term forecasting of consumer credit growth.

Although information criterion-based approaches are easier to compute and have plausible properties, their validity is threatened by the violations of the independence and homoscedasticity assumptions (Arlot and Celisse, 2010; Ahrens et al., 2020). Therefore, another way to determine the tuning parameter is to implement Rigorous LASSO as a routine for data-dependent and theory-driven penalization, so that the parameters are chosen to ensure consistent prediction and estimation. Rigorous LASSO, otherwise known as RLASSO, places greater emphasis on creating more parsimonious models by containing overfitting. At the same time, RLASSO alleviates concerns about the presence of heteroscedastic, non-Gaussian and cluster-dependent error structures (Belloni et al., 2012, 2016). Table 3 depicts the forecast improvement results for the models whose set of controls is selected by the RLASSO tuning parameter. Again, we observe visible improvements in forecast accuracy for total and commercial credit growth, while the short- and long-term horizons for consumer credit growth display significant differences, with minimal (closer to zero) improvements at longer horizons.

A popular way to handle the tuning parameter via data-dependent properties is cross-validation with a grid search. We follow the established practice and design a cross-validation setting where the in-sample estimation data is partitioned into 10-fold tranches, where the first group is used as the validation group and the remaining tranches are taken as the training data. We then fit the LASSO model to the training group, conditional on a given value of the tuning parameter, and compute the mean squared prediction error. This procedure is repeated for each fold to ensure that each data point is utilized once for validation purposes. Accordingly, this process is iterated over a range of potential tuning parameter values to select the one that minimizes the in-sample mean squared prediction error. Table 4 evaluates the forecasting performance of the LASSO model driven by in-sample cross-validation of the λ value, again relative to the factor-augmented model. The estimation results more or less mimic the baseline findings with a noticeable enhancement in forecasting accuracy with respect to the growth rate of total and commercial credits.

The second aspect at the researcher's discretion is the choice among alternative LASSO-based approaches. In this step, we depart from conventional LASSO and adopt an elastic net, which was introduced by Zou and Hastie (2005). LASSO estimation can be affected by the uncertainty in estimating a large covariance matrix, which can be replaced by a shrinkage estimator to ensure that the associated selection process is more robust and stable. In turn, this means imposing an additional L-2 norm constraint on the optimization problem in addition to the original L-1 constraint (Zou and Hastie, 2005; Fan et al., 2015). Elastic net achieves this by leveraging the strengths of LASSO and Ridge Regression with the implementation of a mixture of L-1 (LASSO-type) and L-2 (Ridge-type) penalization. This requires minimizing the following expression, which is shaped by an α parameter (taking values between 0 and 1) that determines the weight of the L-1 vs. L-2 penalization approaches:[11]

$$\frac{1}{n}\sum_{i=1}^{n}(y_i - X_i'\beta)^2 + \frac{\lambda}{n}\left[\alpha\sum_{j=1}^{p}\psi_j|\beta_j| + (1-\alpha)\sum_{j=1}^{p}\psi_j\beta_j^2\right] \tag{4}$$

where $\alpha = 1$ reduces the model to conventional LASSO and $\alpha = 0$ corresponds to traditional ridge regression. n stands for number of observations, λ denotes the usual tuning parameter controlling the overall penalty level and ψ_j represents predictor-specific penalty

[11] For our analysis, we de-facto select the α parameter to be 0.5.

loadings. We report the forecast performance of elastic net relative to the benchmark model in Table 5. The results indicate that we continue to see improvements in predictive performance over the benchmark model for total and commercial credit growth, with relatively moderate improvements for forecasting consumer credit growth up to the 4-month-ahead horizon.

As a final step, we apply the adaptive LASSO method proposed by Zou (2006). The consistency properties of the LASSO model depend on a non-trivial condition of irrepresentability, which imposes strict constraints on the degree of association between the selected predictors and the predictors remaining outside of the model (Zhao and Yu, 2006). Zou (2006) develops a variant of the LASSO-type model ensuring consistency with a weaker set of assumptions. The minimization problem of adaptive LASSO can be summarized as follows:

$$\frac{1}{n}\sum_{i=1}^{n}(y_i - X_i'\beta)^2 + \frac{\lambda}{n}\sum_{j=1}^{p}\hat{\phi}_j|\beta_j| \tag{5}$$

where $\hat{\phi}_j = 1/|\hat{\beta}_{0,j}|^{\theta}$ and $\hat{\beta}_{0,j}$ is an initial estimator like OLS or LASSO itself. Table 6 considers adaptive LASSO as the main model of interest in the recursive forecasting framework and contrasts its performance with a benchmark model for the growth rate of different groups of credits, similar to our previous analyses. Examining the estimation results and summary indicators of forecasting performance, we maintain the argument that the LASSO-type models bring additional forecasting power to the analysis of credit dynamics for total and commercial segments, with slight improvements for consumer credits.

Table 2: Out-of-Sample Predictive Accuracy with Tuning Parameter AIC

Total TL Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.627	0.578	0.554	0.547
	h=5	**h=6**	**h=7**	**h=8**
	0.547	0.539	0.524	0.512
	h=9	**h=10**	**h=11**	**h=12**
	0.511	0.507	0.495	0.494
Commercial TL Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.559	0.483	0.453	0.445
	h=5	**h=6**	**h=7**	**h=8**
	0.432	0.415	0.386	0.355
	h=9	**h=10**	**h=11**	**h=12**
	0.329	0.294	0.261	0.218
Consumer Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.471	0.388	0.326	0.263
	h=5	**h=6**	**h=7**	**h=8**
	0.196	0.119	0.043	-0.027
	h=9	**h=10**	**h=11**	**h=12**
	-0.038	-0.033	0.003	0.021

Notes: This table replicates the analysis in Table 1 with an alternative method to determine the tuning parameter with the help of AIC.

Table 3: Out-of-Sample Predictive Accuracy with Tuning Parameter RLASSO

Total TL Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.606	0.586	0.561	0.545
	h=5	**h=6**	**h=7**	**h=8**
	0.561	0.573	0.584	0.606
	h=9	**h=10**	**h=11**	**h=12**
	0.625	0.636	0.644	0.659
Commercial TL Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.518	0.472	0.465	0.451
	h=5	**h=6**	**h=7**	**h=8**
	0.457	0.451	0.434	0.425
	h=9	**h=10**	**h=11**	**h=12**
	0.412	0.406	0.416	0.387
Consumer Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.420	0.366	0.309	0.269
	h=5	**h=6**	**h=7**	**h=8**
	0.225	0.150	0.088	0.047
	h=9	**h=10**	**h=11**	**h=12**
	0.018	0.008	0.021	0.034

Notes: This table replicates the analysis in Table 1 with an alternative method to determine the tuning parameter with the help of RLASSO.

Table 4: Out-of-Sample Predictive Accuracy with Tuning Parameter Cross-Validation

Total TL Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.631	0.571	0.556	0.554
	h=5	**h=6**	**h=7**	**h=8**
	0.556	0.555	0.548	0.546
	h=9	**h=10**	**h=11**	**h=12**
	0.558	0.558	0.551	0.554
Commercial TL Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.552	0.490	0.444	0.440
	h=5	**h=6**	**h=7**	**h=8**
	0.434	0.418	0.396	0.358
	h=9	**h=10**	**h=11**	**h=12**
	0.331	0.302	0.264	0.221
Consumer Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.448	0.346	0.248	0.135
	h=5	**h=6**	**h=7**	**h=8**
	0.041	-0.006	-0.021	-0.053
	h=9	**h=10**	**h=11**	**h=12**
	-0.101	-0.141	-0.176	-0.200

Notes: This table replicates the analysis in Table 1 with an alternative method to determine the tuning parameter with the help of cross-validation.

Table 5: Out-of-Sample Predictive Accuracy with LASSO Method Elastic Net

Total TL Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.621	0.571	0.547	0.548
	h=5	**h=6**	**h=7**	**h=8**
	0.558	0.558	0.562	0.565
	h=9	**h=10**	**h=11**	**h=12**
	0.570	0.577	0.574	0.561
Commercial TL Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.562	0.492	0.470	0.479
	h=5	**h=6**	**h=7**	**h=8**
	0.476	0.472	0.461	0.425
	h=9	**h=10**	**h=11**	**h=12**
	0.387	0.347	0.294	0.242
Consumer Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.430	0.343	0.274	0.211
	h=5	**h=6**	**h=7**	**h=8**
	0.126	0.020	-0.079	-0.176
	h=9	**h=10**	**h=11**	**h=12**
	-0.224	-0.245	-0.254	-0.259

Notes: This table replicates the analysis in Table 1 with an alternative LASSO specification shaped by the elastic net method.

Table 6: Out-of-Sample Predictive Accuracy with LASSO Method Adaptive LASSO

Total TL Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.633	0.593	0.584	0.578
	h=5	**h=6**	**h=7**	**h=8**
	0.585	0.585	0.590	0.604
	h=9	**h=10**	**h=11**	**h=12**
	0.620	0.624	0.634	0.652
Commercial TL Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.573	0.552	0.534	0.532
	h=5	**h=6**	**h=7**	**h=8**
	0.526	0.528	0.506	0.478
	h=9	**h=10**	**h=11**	**h=12**
	0.446	0.403	0.363	0.315
Consumer Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.452	0.374	0.273	0.195
	h=5	**h=6**	**h=7**	**h=8**
	0.117	0.013	-0.072	-0.119
	h=9	**h=10**	**h=11**	**h=12**
	-0.152	-0.134	-0.097	-0.041

Notes: This table replicates the analysis in Table 1 with an alternative LASSO specification shaped by the adaptive LASSO method.

IV.III. Robustness Checks

As with any other forecasting exercise, the power of our results may be diminished by issues of sample coverage and the choice of benchmark model. We undertake a battery of robustness checks to address any concerns about sample composition and benchmark modeling. In Table 7, we proceed with a smaller sample set of banks by omitting state-owned entities. Previous literature shows that the spatial and cyclical expansion of state-owned banks' credit may be driven by an entirely different set of factors than those of private and foreign banks (Cull and Xu, 2003; Önder and Özyıldırım, 2013; Bertay et al., 2015). In our baseline empirical strategy, we try to use a relatively long and stable in-sample estimation interval (from January 2012 to December 2019) to better approximate the existing relationships between credit growth and macro-financial predictors. However, this may limit the informativeness with respect to recent episodes. In Table 8, concerning the recursive forecasts, we repeat all the estimations with a shorter in-sample estimation period, ranging from January 2015 to December 2019. Similarly, in Table 9, we shorten the original out-of-sample forecasting period by starting it from January 2021 onwards (instead of from January 2020 onwards). The results of these robustness analyses are broadly consistent with the main empirical findings.

Despite the fact that it is rather erratic and somewhat difficult to predict, for the sake of completeness, we further analyze the month-on-month credit growth. In the original setting, we apply an annual transformation procedure to all the control variables in order to ensure consistency, so this particular robustness check also involves the monthly transformation of the covariates. In Table 10, when examining monthly growth (or change) dynamics, we observe that the LASSO method still improves the forecasting of total and commercial credit growth, but the accuracy gains are visibly moderate for the latter.

Moreover, we replace the benchmark model of factor-augmented regression with two alternatives. Instead of building a factor-augmented model with two principal components derived from a separate implementation of PCA on contemporaneous and lagged values of the explanatory variables, we decide to build a so-called "Enhanced Factor-Augmented" model with six principal components derived from a similar implementation. In Table 11, the relative predictive power of the LASSO model for total and commercial credits is intact against the aforementioned benchmark. We also employ another benchmark with the best subset selection features in the form of a backward stepwise regression model. In Table 12, we achieve similar results except for the decreasing level of improvement at shorter horizons (up to four months). In Table A2 of the Appendix, we also employ AIC-based iterative model as another benchmark model. We still continue to document superior predictive performance of LASSO-based modeling choice when the third alternative benchmark model specification is considered.

Table 7: Robustness Checks Excluding State Banks

Total TL Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.574	0.523	0.506	0.525
	h=5	**h=6**	**h=7**	**h=8**
	0.562	0.583	0.593	0.618
	h=9	**h=10**	**h=11**	**h=12**
	0.642	0.657	0.657	0.669
Commercial TL Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.475	0.392	0.354	0.331
	h=5	**h=6**	**h=7**	**h=8**
	0.361	0.387	0.375	0.328
	h=9	**h=10**	**h=11**	**h=12**
	0.274	0.210	0.142	0.066
Consumer Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.335	0.156	0.023	-0.107
	h=5	**h=6**	**h=7**	**h=8**
	-0.203	-0.281	-0.335	-0.351
	h=9	**h=10**	**h=11**	**h=12**
	-0.328	-0.298	-0.263	-0.230

Notes: This table replicates the analysis in Table 1 for a revised sample that excludes state-owned banks.

Table 8: Robustness Checks Using Shorter Estimation Sample Period from January 2015 to December 2019

Total TL Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.649	0.621	0.608	0.589
	h=5	**h=6**	**h=7**	**h=8**
	0.590	0.588	0.581	0.594
	h=9	**h=10**	**h=11**	**h=12**
	0.598	0.599	0.602	0.613
Commercial TL Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.526	0.472	0.447	0.436
	h=5	**h=6**	**h=7**	**h=8**
	0.485	0.495	0.489	0.484
	h=9	**h=10**	**h=11**	**h=12**
	0.465	0.450	0.431	0.405
Consumer Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.458	0.326	0.187	0.050
	h=5	**h=6**	**h=7**	**h=8**
	-0.029	-0.115	-0.219	-0.286
	h=9	**h=10**	**h=11**	**h=12**
	-0.311	-0.310	-0.311	-0.307

Notes: This table replicates the analysis in Table 1 for a revised sample by shortening the initial in-sample estimation period to January 2015-December 2019.

Table 9: Robustness Checks Using Shorter Forecasting Sample Period from January 2021 to June 2023

Total TL Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.551	0.532	0.548	0.576
	h=5	**h=6**	**h=7**	**h=8**
	0.603	0.617	0.631	0.653
	h=9	**h=10**	**h=11**	**h=12**
	0.677	0.681	0.685	0.693
Commercial TL Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.504	0.508	0.493	0.507
	h=5	**h=6**	**h=7**	**h=8**
	0.519	0.528	0.511	0.482
	h=9	**h=10**	**h=11**	**h=12**
	0.464	0.452	0.421	0.389
Consumer Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.335	0.111	-0.145	-0.393
	h=5	**h=6**	**h=7**	**h=8**
	-0.539	-0.659	-0.768	-0.823
	h=9	**h=10**	**h=11**	**h=12**
	-0.825	-0.813	-0.754	-0.687

Notes: This table replicates the analysis in Table 1 for a revised sample by shortening the initial out-of-sample forecasting period to January 2021-June 2023.

Table 10: Robustness Checks Using Monthly Credit Growth

Total TL Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.344	0.325	0.315	0.354
	h=5	**h=6**	**h=7**	**h=8**
	0.325	0.323	0.316	0.333
	h=9	**h=10**	**h=11**	**h=12**
	0.376	0.388	0.411	0.363
Commercial TL Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.117	0.088	0.062	0.113
	h=5	**h=6**	**h=7**	**h=8**
	0.124	0.098	0.048	0.031
	h=9	**h=10**	**h=11**	**h=12**
	0.094	0.090	0.096	0.072
Consumer Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	-0.035	0.022	-0.009	0.007
	h=5	**h=6**	**h=7**	**h=8**
	0.010	-0.003	-0.044	-0.053
	h=9	**h=10**	**h=11**	**h=12**
	-0.008	0.026	0.032	-0.020

Notes: This table replicates the analysis in Table 1 by considering month-on-month credit growth instead of year-on-year credit growth.

Table 11: Robustness Checks Using Enhanced Factor-Augmented Model as Alternative Benchmark Specification

Total TL Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.607	0.577	0.571	0.568
	h=5	**h=6**	**h=7**	**h=8**
	0.560	0.560	0.564	0.575
	h=9	**h=10**	**h=11**	**h=12**
	0.590	0.586	0.585	0.596
Commercial TL Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.586	0.564	0.544	0.538
	h=5	**h=6**	**h=7**	**h=8**
	0.544	0.560	0.552	0.526
	h=9	**h=10**	**h=11**	**h=12**
	0.503	0.479	0.435	0.405
Consumer Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.326	0.205	0.056	-0.100
	h=5	**h=6**	**h=7**	**h=8**
	-0.244	-0.369	-0.492	-0.589
	h=9	**h=10**	**h=11**	**h=12**
	-0.655	-0.705	-0.693	-0.671

Notes: This table replicates the analysis in Table 1 by considering an alternative benchmark model in the form of enhanced factor-augmented model.

Table 12: Robustness Checks Using Stepwise Regression Model as Alternative Benchmark Specification

Total TL Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.060	0.041	0.038	0.069
	h=5	**h=6**	**h=7**	**h=8**
	0.098	0.185	0.256	0.313
	h=9	**h=10**	**h=11**	**h=12**
	0.357	0.380	0.406	0.453
Commercial TL Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.030	0.070	0.077	0.077
	h=5	**h=6**	**h=7**	**h=8**
	0.153	0.230	0.282	0.282
	h=9	**h=10**	**h=11**	**h=12**
	0.299	0.342	0.347	0.369
Consumer Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	-0.026	-0.102	-0.195	-0.243
	h=5	**h=6**	**h=7**	**h=8**
	-0.242	-0.248	-0.267	-0.245
	h=9	**h=10**	**h=11**	**h=12**
	-0.277	-0.298	-0.312	-0.327

Notes: This table replicates the analysis in Table 1 by considering an alternative benchmark model in the form of stepwise regressions.

IV.IV. Findings for Other Credit Sub-Categories

In addition to assessing forecast performance for the aggregate credit outlook, our methodology and data source also allow us to examine different sub-categories of credits. We extract the bank-level SME and large firm credit growth for commercial segment, combined with general-purpose, housing, and vehicle credit growth for the consumer segment. In Table 13, we document that the superiority of LASSO approach is particularly evident for SME credit growth at all horizons, and is found for large-firm credit growth only at shorter horizons (one- and two-month-ahead). Turning to the consumer segment, improvements in forecasting are evident at short-term horizons for general-purpose and vehicle loan growth.

Table 13: Out-of-Sample Predictive Accuracy for Credit Sub-Categories

SME Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.620	0.591	0.573	0.571
	h=5	**h=6**	**h=7**	**h=8**
	0.578	0.582	0.586	0.595
	h=9	**h=10**	**h=11**	**h=12**
	0.613	0.613	0.615	0.622
Large Firm Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.244	0.112	-0.013	-0.124
	h=5	**h=6**	**h=7**	**h=8**
	-0.125	-0.152	-0.184	-0.247
	h=9	**h=10**	**h=11**	**h=12**
	-0.334	-0.396	-0.487	-0.585
General-Purpose Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.404	0.325	0.205	0.076
	h=5	**h=6**	**h=7**	**h=8**
	-0.053	-0.250	-0.437	-0.601
	h=9	**h=10**	**h=11**	**h=12**
	-0.774	-0.950	-1.125	-1.323
Housing Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	-0.447	-0.933	-1.127	-1.242
	h=5	**h=6**	**h=7**	**h=8**
	-1.453	-1.924	-2.877	-3.267
	h=9	**h=10**	**h=11**	**h=12**
	-3.255	-3.457	-3.376	-3.762
Vehicle Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.217	0.165	0.112	0.060
	h=5	**h=6**	**h=7**	**h=8**
	0.026	0.001	0.001	-0.003
	h=9	**h=10**	**h=11**	**h=12**
	0.000	0.012	0.023	0.038

Notes: This table replicates the analysis in Table 1 for sub-components of commercial and consumer credit segments.

IV.V. An Application: Residual Credit and Inflationary Pressures

Thus far, we have attempted to show the predictive ability of the LASSO variable selection method for the credit growth rate against alternative models and across different settings. In this section, we briefly focus on a case study to demonstrate how this method can be essentially operationalized to address another important concern (from a financial stability perspective), which is articulated as quantifying the disparity between recorded credit growth and the level suggested by the prevailing macroeconomic and financial conditions. To this end, we first implement LASSO variable selection to obtain a proposed specification by using the data for the period January 2012-December 2019. We then take the corresponding relationships with respect to the selected predictors as given and estimate a panel regression to construct implied credit growth levels for another period of interest, January 2020-June 2023. Accordingly, we define the residual credit indicator at the bank level, which reflects the differences between the actual and implied credit growth rate, in order to identify periods of abnormal lending (either expansionary or contractionary):

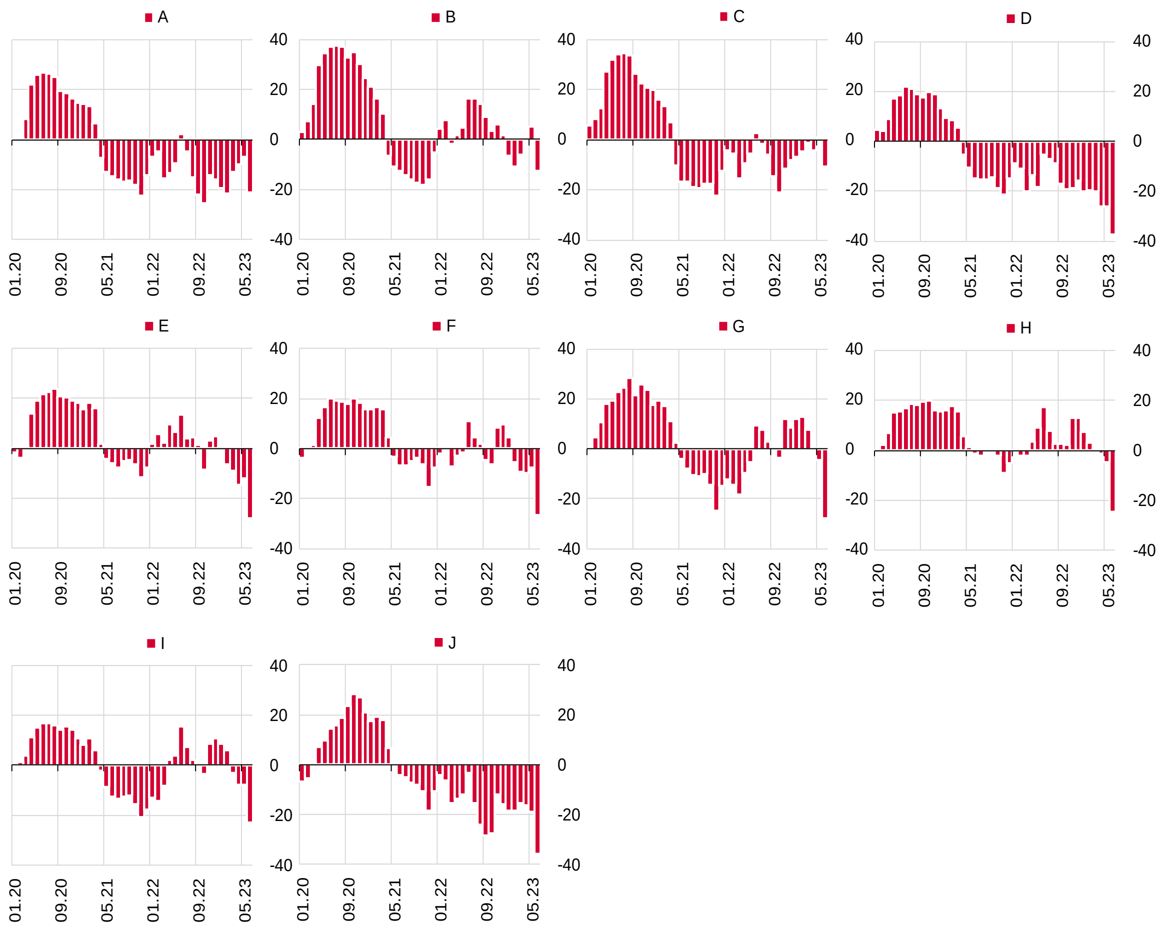
$$Residual\ Credit = Actual\ Credit\ Growth - Credit\ Growth_{LASSO-Implied} \quad (6)$$

Figure 2 shows the evolution of the residual credit indicator for each sample bank (again in a masked fashion). Overall, we observe a certain degree of heterogeneity across individual banks regarding irregular credit growth relative to the level suggested by fundamentals.[12]

In addition to monitoring purposes, such an indicator can also be employed as an input for further econometric analysis in order to relate abnormal credit movements to a variety of factors. In the context of this section, we conduct a basic case study analyzing the relationship between residual credit and inflationary pressures. The Turkish case provides a useful setting for investigating this relationship, as the country has experienced sharp and prolonged upward pressures on price formation since 2020. Against this background, the question of whether such pressures have had secondary effects on financial stability through rapid increases in credit use by households and firms comes to the fore with respect to its policy implications. The following part of this section undertakes a formal analysis to shed more light on this debate using the residual credit indicator.

[12] Overall, we observe that there exists a considerable divergence of the excess credit, deviating from the level implied by macro-financial conditions and bank conditions, in terms of bank ownership structure. This is manifested in the form of highly positive residual credit recorded for state-owned banks during early 2020 and onwards. We argue that such a clustering for state banks is mostly related to the fact that credits granted by state banks during that period were mostly for the purpose of offsetting the potential adverse effects of Covid-19 on financial intermediation and economic activity.

Figure 2: Bank-Level Residual Credit Indicator



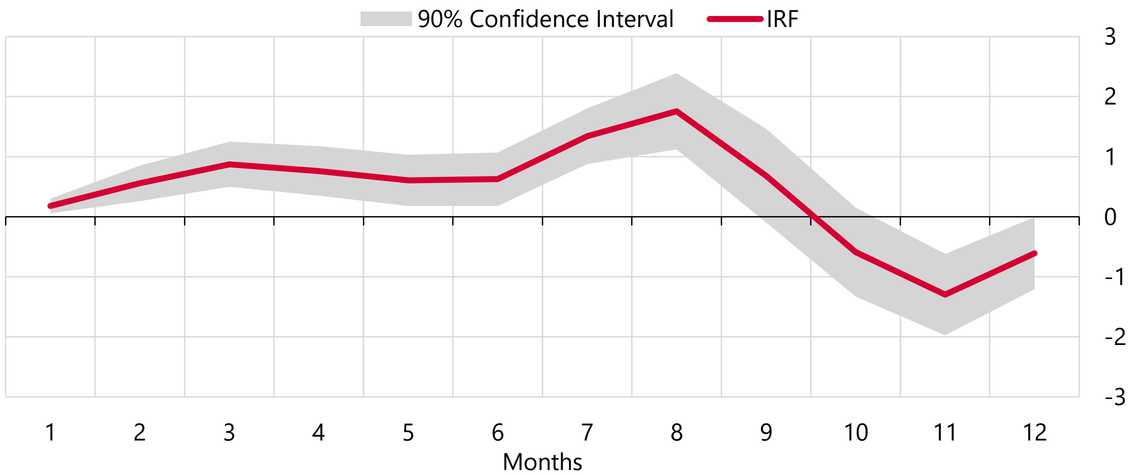
Notes: This figure illustrates the bank-level distribution of the residual credit indicator for the period January 2020-June 2023. The sample comprises the 10 largest banks operating in the Turkish banking industry, which are denoted by A to J in a masked fashion. The association between credit growth and macro-financial dynamics is extracted by the implementation of LASSO variable selection by using the data for the period January 2012-December 2019 and reflecting those dynamics to the aforementioned examined period.

We investigate the dynamic relations between residual credit and inflation by exploiting impulse response functions (IRF) (response of abnormal credit movements to shocks in inflation) for the period January 2020-June 2023. We use the local projection method developed by Jordà (2005) as a popular method for composing IRFs. With the help of this method, we estimate local projections by calculating the coefficients of IRFs for each period using a panel regression model with fixed effects rather than extrapolating into increasingly distant horizons from a given model, as it is done with vector autoregressions (VAR). As suggested by Jordà (2005), local projections are more robust to misspecifications and easily accommodate highly nonlinear and flexible specifications. The model can be defined as follows:

$$Residual\ Credit_{i,t+h} = \alpha_{1h} \sum_{l=0}^{3} \Delta INF_{t-l} + \mu_i + \varepsilon_{i,th} \tag{7}$$

where $i = 1, \dots, N$ refers to the banks, and $t = 1, \dots, T$ refers to time period (month-by-year). $\varepsilon_{i,t}$ is a noise error. μ_i represents bank fixed effects. $Residual\ Credit_{i,t+h}$ denotes the residual credit indicator for bank i at time t whereas h signifies the horizon up to 12 months. $\Delta INF_{i,t-l}$ describes the first difference of inflation with l demonstrating the number of lags.[13] Figure 3 illustrates the cumulative response of residual credit to an impulse applied to inflation. We find that a positive shock on inflation at time t significantly increases the credit residuals approximately over a nine-month period followed by a gradual fading of the effect. This shows that, under inflationary pressures, firms and households tend to elevate the credit use at short- and medium-term horizons accompanied by a correction movement in the long-term credit financing. Hence, sudden and strong price increases could have disruptive implications on financial stability, especially in short-term.

Figure 3: IRF of Residual Credit to an Inflation Shock by Local Projection Estimations



V. Conclusion

Credit growth has long been recognized as a useful indicator for understanding the progress of financial deepening and the build-up of risks to financial stability. A weaker trend in credit growth could imply that economic agents are facing problems in accessing the flow of funds to finance consumption and investment, which could ultimately lead to lower-than-potential economic growth, productivity, earnings and welfare. On the other hand, the literature shows that excessive credit movements in the form of broadly positive credit growth (relative to economic growth) are a prime predictor of impending financial instability. Abnormal financial intermediation activities, reflected in credit growth that deviates from what is implied by macro-financial dynamics, could lead to unwarranted leverage of households and non-financial firms, which in turn could exacerbate credit risk and financial contagion. This situation is particularly relevant in an emerging market environment, which is characterized by

[13] In our main local projection analysis, we use three-months lag structure but our IRF results do not vary considerably with alternative lag choices.

a heavy reliance on the banking sector for financing and a relatively shorter and less stable average financial cycle (compared to advanced economies). Therefore, timely monitoring and accurate forecasting of credit growth is essential for policymakers and practitioners in the context of Türkiye and other emerging markets.

Similar to assessing the future course of other common variables, forecasting credit growth is also constrained by a limitation of dimensionality problem. Building linear predictive models to obtain more accurate forecasts necessitates the selection of a handful of predictors from broader data sets. In this study, we propose the application of regularization and shrinkage regressions, namely LASSO-class models, to obtain a sparse solution for analyzing credit growth at the bank level. In particular, we test the predictive power of the LASSO method against a benchmark model concerning total, commercial, and consumer credit growth through pseudo-out-of-sample recursive forecasting exercises. The main findings reinforce the idea that the use of the LASSO model can bring additional benefits for better forecasting of credit growth relative to widely used factor models. Our results are shown to withstand additional robustness checks and tests. Furthermore, when we analyze the dynamic relationship between residual credit and inflation using the local projection method, we find that an inflationary shock has a positive and statistically significant effect on abnormal credit movements.

The findings of this study have several implications for policymakers and regulators regarding financial stability. First, as shown in our analyses, the LASSO variable selection can be used to construct a bank-level time-varying residual credit indicator that enables authorities to monitor and quantify the dispersion between credit growth and the level implied by the contemporary macro-financial outlook (derived from a parsimonious model specification obtained via LASSO). Not only does this proxy have the potential to be used for reporting purposes (e.g. Financial Stability Report), but the related indicator can also be employed as an input for econometric analysis, as we illustrate in this paper to explore the relationship between excess credit movements and inflationary pressures. Second, depending on the availability of scenarios for selected macro-financial variables, the modeling approach in this paper can be further used to produce forecasts of bank-level credit growth under different scenarios. Last but not least, as a potential third area of extension and implementation, LASSO variable selection can be used to calibrate satellite panel models integrated into widely popular stress testing frameworks in order to transmit local and global macro-level shocks to bank-level behavior (e.g. credit growth, non-performing loans ratio etc.). This could enhance the informative nature of any stress test design applied to the Turkish banking industry to reveal the impact of shocks on bank outcomes of regulatory interest such as capital adequacy and asset quality.

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Appendix

Table A1: Data Definitions

Abbreviations	Definitions	Level of Observations
GDPry_yg	Annual Real GDP Growth (Annualized)	Macro
GDPny_yg	Annual Nominal GDP Growth (Annualized)	Macro
GDPrq_yg	Annual Real GDP Growth (Compared to the Same Quarter of the Previous Year)	Macro
GDPnq_yg	Annual Nominal GDP Growth (Compared to the Same Quarter of the Previous Year)	Macro
CPI_yg	CPI Annual Growth (Percent)	Macro
PPI_yg	PPI Annual Growth (Percent)	Macro
IPI_TA_yg	IPI Annual Growth (Calendar Adjusted, Percent)	Macro
Turnover_TA_yg	Turnover Index Annual Growth (Calendar Adjusted, Percent)	Macro
M3_yg	Annual Growth in M3 Money Supply (Percent)	Macro
PublicDebtStock_yg	Annual Growth in Central Government Debt Stock (Percent)	Macro
TLCommercial_yg	TL Commercial Loan Annual Growth (Percent)	Bank-Level
FXCommercial_yg	FX Commercial Loan Annual Growth (Percent)	Bank-Level
FXCommercialUSD_yg	Annual Growth in FX Commercial Loans (in USD, Percent)	Bank-Level
TLPersonalFinance_yg	TL Personal Finance Loan Annual Growth (Percent)	Bank-Level
TLDeposit_yg	TL Deposits Annual Growth (Percent)	Bank-Level
FXDeposit_yg	Annual Growth in FX Deposits (Percent)	Bank-Level
FXDepositUSD_yg	Annual Growth in FX Commercial Loans (in USD, Percent)	Bank-Level
TotalDeposit_yg	Total Deposits Annual Growth (Percent)	Bank-Level
USDTRY_yg	USD Currency Annual Growth (Percent)	Macro
BasketCurrency_yg	Basket Currency Annual Growth (Percent)	Macro
FXDebt_yg	Annual Growth in Foreign Currency Denominated Debt (Percent)	Bank-Level
FXDebtUSD_yg	Annual Growth in Foreign Currency Denominated Debt (in USD, Percent)	Bank-Level
TotalFreeSP_yg	Annual Growth of Total Free Securities Portfolio (Percent)	Bank-Level
TotalLiquidAssets_yg	Annual Growth in Total Liquid Assets (Percent)	Bank-Level
TLRetail_yg	TL Retail Loan Annual Growth (Percent)	Bank-Level
TotalLoan_yg	Total Loan Annual Growth (Percent)	Bank-Level

TLLoan_yg	TL Loan Annual Growth (Percent)	Bank-Level
FXLoan_yg	FX Loan Annual Growth (Percent)	Bank-Level
FXLoanUSD_yg	FX Loan Annual Growth (in USD, Percent)	Bank-Level
TLSME_yg	TL SME Loan Annual Growth (Percent)	Bank-Level
FXSME_yg	FX SME Loan Annual Growth (Percent)	Bank-Level
TLLargeFirm_yg	TL Large Scale Firm Loan Annual Growth (Percent)	Bank-Level
TotalSME_yg	Total SME Loan Annual Growth (Percent)	Bank-Level
TLRetailexcPCC_yg	TL Retail (Excluding PCC) Loan Annual Growth (Percent)	Bank-Level
TLGeneralPurpose_real_yg	TL Personal Loan Real Annual Growth (Percent)	Bank-Level
TLCommercial_real_yg	TL Commercial Loan Real Annual Growth (Percent)	Bank-Level
TLRetail_real_yg	TL Retail Loan Real Annual Growth (Percent)	Bank-Level
RSVI_ta_yg	Retail Sales Volume Index Annual Growth (Calendar Adjusted, Percent)	Macro
dy_PPI_yg	Difference in PPI Annual Growth (Percent Point)	Macro
FXDebttoLiability	Ratio of FX Debt to Liabilities (Percent)	Bank-Level
DollarizationRate	Share of FX Deposits in Total Deposits (Percent)	Bank-Level
dy_CPI_yg	CPI Annual Growth Annual Difference (Percent Point)	Macro
dy_CDS	CDS Annual Difference (Basis Point)	Macro
dy_REER_CPI	CPI Based Real Effective Exchange Rate Annual Difference (Percent Point)	Macro
dy_REER_PPI	PPI Based Real Effective Exchange Rate Annual Difference (Percent Point)	Macro
dy_ImpliedVol	Annual Difference of Implied Volatility	Macro
dy_CUR_MA	Annual Difference in Capacity Utilization Rate (Seasonally Adjusted)	Macro
dy_DollarizationRate	Annual Difference in the Share of FX Deposits in Total Deposits (Percent)	Bank-Level
dy_VIX	VIX Annual Difference	Macro
dy_WAFC	Annual Difference of Weighted Average Funding Cost (Percent Point)	Macro
dy_avgdurationpf	Annual Difference in the Average Duration of Personal Finance Loans (in months)	Bank-Level
avgdurationpf	Average Duration of Personal Loans (in months)	Bank-Level
capitalflows1y_GDP	Ratio of Total Portfolio and Other Investments to GDP (Annualized, Percent)	Macro
capitalflows2y_GDP	Ratio of Total Direct, Portfolio and Other Investments to GDP (Annualized, Percent)	Macro
CAD_GDP	Ratio of Current Account Deficit to GDP (Annualized, Percent)	Macro
BudgetDeficit_GDP	Ratio of Central Government Budget Deficit to GDP (Annualized, Percent)	Macro

PublicDebt_GDP	Ratio of Central Government Debt Stock to GDP (Percent)	Macro
employment_rate	Employment Rate (Percent)	Macro
unemployment_rate	Unemployment Rate (Percent)	Macro
dy_employment_rate	Annual Difference in Employment Rate (Percent)	Macro
dy_unemployment_rate	Annual Difference in Unemployment Rate (Percent)	Macro
requiredreserve_ratio	Ratio of Required Reserves to Liabilities (Percent)	Bank-Level
personalfinance_npl_ratio	Share of Non-Performing Loans in Personal Finance Loans (Percent)	Bank-Level
retail_npl_ratio	Share of Non-Performing Loans in Retail Loans (Percent)	Bank-Level
commercial_npl_ratio	Share of Non-Performing Loans in Commercial Loans (Percent)	Bank-Level
total_npl_ratio	Share of Non-Performing Loans in Total Loans (Percent)	Bank-Level
totalloan_collection_addition	Ratio of 12-Month Total NPL Collections to 12-Month Total Net NPL Additions in Total Loans (Percent)	Bank-Level
commercialloan_collection_addition	Ratio of 12-Month Total NPL Collections to 12-Month Total Net NPL Additions in Commercial Loans (Percent)	Bank-Level
retailloan_collection_addition	Ratio of 12-Month Total NPL Collections to 12-Month Total Net NPL Additions in Retail Loans (Percent)	Bank-Level
pfloan_collection_addition	Ratio of 12-Month Total NPL Collections to 12-Month Total Net NPL Additions in Personal Finance Loans (Percent)	Bank-Level
totalloan_collection_npl	Ratio of 12-Month Total NPL Collections to 12-Month Average NPL Balance in Total Loans (Percent)	Bank-Level
commercialloan_collection_npl	Ratio of 12-Month Total NPL Collections to 12-Month Average NPL Balance in Commercial Loans (Percent)	Bank-Level
retailloan_collection_npl	Ratio of 12-Month Total NPL Collections to 12-Month Average NPL Balance in Retail Loans (Percent)	Bank-Level
pfloan_collection_npl	Ratio of 12-Month Total NPL Collections to 12-Month Average NPL Balance in Personal Finance Loans (Percent)	Bank-Level
car	Capital Adequacy Ratio (Percent)	Bank-Level
roe_o	Return on Average Equity (Annualized, Percent)	Bank-Level
SP_assets	Ratio of Securities Portfolio to Assets (Percent)	Bank-Level
freeSP_ assets	Ratio of Free Securities Portfolio to Assets (Percent)	Bank-Level
colSP_assets	Ratio of Securities Portfolio Held Bank-Level as Collateral to Assets (Percent)	Bank-Level
liquid_assets	Ratio of Liquid Assets to Total Assets (Percent)	Bank-Level
c_d	Loan to Deposit Ratio (Percent)	Bank-Level
credit_demand	Credit Tendency Survey Past 3 Months	Macro
credit_demand_exp	Credit Tendency Survey Expectations for the Next 3 Months	Macro
TLComm_STShare_ODACCinc	Share of Short-Term Loans in TL Commercial Loans (Including ODA and Credit Cards) (Percent)	Bank-Level
TLComm_STShare_ODACCexc	Share of Short-Term Loans in TL Commercial Loans (Excluding ODA and Credit Cards) (Percent)	Bank-Level
TLConsumer_STShare_ODAinc	Share of Short-Term Loans in TL Consumer Loans (Including ODA and Credit Cards) (Percent)	Bank-Level

TLConsumer _STShare_ODaexc	Share of Short-Term Loans in TL Consumer Loans (Excluding ODA and Credit Cards) (Percent)	Bank-Level
TLHousing_STShare	Share of Short-Term Loans in TL Housing Loans (Percent)	Bank-Level
TLVehicle_STShare	Share of Short-Term Loans in TL Vehicle Loans (Percent)	Bank-Level
TLPF_STShare_ODAinc	Share of Short-Term Loans in TL Personal Finance Loans (Including ODA) (Percent)	Bank-Level
TLPF_STShare_ODAexc	Share of Short-Term Loans in TL Personal Finance Loans (Excluding ODA) (Percent)	Bank-Level
TLPCC_STShare	Share of Short-Term Loans in TL Personal Credit Cards (Percent)	Bank-Level
TLRetail_STShare_ODAinc	Share of Short-Term Loans in TL Retail Loans (Including ODA) (Percent)	Bank-Level
TLRetail_STShare_ODAexc	Share of Short-Term Loans in TL Retail Loans (Excluding ODA) (Percent)	Bank-Level
TLTotalLoan_STShare	Share of Short-Term Loans in TL Total Loans (Percent)	Bank-Level
TLCommIntMargin_ODACCinc	Difference between TL Commercial Interest (Including Overdraft and Credit Card) and TL Deposit Interest (Percent Point)	Bank-Level
TLCommIntMargin_ODACCexc	Difference between TL Commercial Interest (Excluding ODA and Credit Card) and TL Deposit Interest (Percent Point)	Bank-Level
TLCommRealInt_ODACCinc	Difference between TL Commercial Interest (Including Overdraft and Credit Card) and CPI (Percent Point)	Bank-Level
TLCommRealInt_ODACCexc	Difference between TL Commercial Interest (Excluding Overdraft and Credit Card) and CPI (Percent Point)	Bank-Level
TLCommExpRealInt_ODACCinc	Difference between TL Commercial Rates (Including ODA and Credit Card) and 12-Month CPI Expectation (Percent Point)	Bank-Level
TLCommExpRealInt_ODACCexc	Difference between TL Commercial Rates (Excluding ODA and Credit Card) and 12-Month CPI Expectation (Percent Point)	Bank-Level
TLSMEIntMargin_ODACCinc	Difference between TL SME Interest (including ODA and Credit Card) and TL Deposit Interest (Percent Point)	Bank-Level
TLSMEIntMargin_ODACCexc	Difference between TL SME Interest (Excluding Overdraft and Credit Card) and TL Deposit Interest (Percent Point)	Bank-Level
TLSMERealInt_ODACCinc	Difference between TL SME Interest (Including Overdraft and Credit Card) and CPI (Percent Point)	Bank-Level
TLSMERealInt_ODACCexc	Difference between TL SME Interest (Excluding Overdraft and Credit Card) and CPI (Percent Point)	Bank-Level
TLSMEExpRealInt_ODACCinc	Difference between TL SME Interest Rates (including ODA and Credit Card) and 12-Month CPI Expectation (Percent Point)	Bank-Level
TLSMEExpRealInt_ODACCexc	Difference between TL SME Interest Rates (Excluding ODA and Credit Card) and 12-Month CPI Expectation (Percent Point)	Bank-Level
TLLFIntMargin_ODACCinc	Difference between TL Large Scale Firm Interest Rates (including ODA and Credit Card) and TL Deposit Rates (Percent Point)	Bank-Level
TLLFIntMargin_ODACCexc	Difference between TL Large Scale Firm Interest Rates (Excluding ODA and Credit Card) and TL Deposit Rates (Percent Point)	Bank-Level
TLLFRealInt_ODACCinc	TL Difference between Interest Rates (Including Overdraft and Credit Card) and CPI (Percent Point)	Bank-Level
TLLFRealInt_ODACCexc	TL Large Company Interest (Excluding Overdraft and Credit Card) and CPI (Percent Point)	Bank-Level
TLLFExpRealInt_ODACCinc	Difference between TL Large Scale Firm Interest Rates (including ODA and Credit Card) and 12-Month CPI Expectation (Percent Point)	Bank-Level
TLLFExpRealInt_ODACCexc	Difference between TL Large Scale Firm Interest Rates (Excluding ODA and Credit Card) and 12-Month CPI Expectation (Percent Point)	Bank-Level
TLPFIntMargin_ODAinc	Difference between TL Personal Finance Interest (Including Overdraft) and TL Deposit Interest (Percent Point)	Bank-Level
TLPFIntMargin_ODAexc	Difference between TL Personal Finance Interest (Excluding ODA) and TL Deposit Interest (Percent Point)	Bank-Level
TLPFRealInt_ODAinc	Difference between TL Personal Finance Interest (Including Overdraft) and CPI (Percent Point)	Bank-Level

TLPFRealInt_ODAexc	Difference between TL Personal Finance Interest (Excluding Overdraft) and CPI (Percent Point)	Bank-Level
TLPFExpRealInt_ODAinc	Difference between TL Personal Finance Rates (Including ODA) and 12-Month CPI Expectation (Percent Point)	Bank-Level
TLPFExpRealInt_ODAexc	Difference between TL Personal Finance Rates (Excluding ODA) and 12-Month CPI Expectation (Percent Point)	Bank-Level
TLRetailIntMargin_ODAinc	Difference between TL Retail Interest (including ODA) and TL Deposit Interest (Percent Point)	Bank-Level
TLRetailIntMargin_ODAexc	Difference between TL Retail Interest (Excluding ODA) and TL Deposit Interest (Percent Point)	Bank-Level
TLRetailRealInt_ODAinc	Difference between TL Retail Interest (including ODA) and CPI (Percent Point)	Bank-Level
TLRetailRealInt_ODAexc	Difference between TL Retail Interest (Excluding ODA) and CPI (Percent Point)	Bank-Level
TLRetailExpRealInt_ODAinc	Difference between TL Retail Interest Rates (including ODA) and 12-Month CPI Expectation (Percent Point)	Bank-Level
TLRetailExpRealInt_ODAexc	Difference between TL Retail Interest Rates (Excluding ODA) and 12-Month CPI Expectation (Percent Point)	Bank-Level

Notes: This table lists the total predictor pool used for the LASSO variable selection procedure. The one period lagged versions of these variables are also included in the broader predictor set.

Table A2: Robustness Checks Using AIC-Based Iterative Model as Alternative Benchmark Specification

Total TL Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.078	0.078	0.104	0.181
	h=5	**h=6**	**h=7**	**h=8**
	0.180	0.194	0.224	0.233
	h=9	**h=10**	**h=11**	**h=12**
	0.303	0.308	0.323	0.339
Commercial TL Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.024	-0.031	0.028	0.102
	h=5	**h=6**	**h=7**	**h=8**
	0.156	0.209	0.258	0.261
	h=9	**h=10**	**h=11**	**h=12**
	0.284	0.301	0.306	0.307
Consumer Loan Growth	**h=1**	**h=2**	**h=3**	**h=4**
	0.010	-0.074	-0.137	-0.178
	h=5	**h=6**	**h=7**	**h=8**
	-0.157	-0.130	-0.117	-0.090
	h=9	**h=10**	**h=11**	**h=12**
	-0.088	-0.110	-0.126	-0.174

Notes: This table replicates the analysis in Table 1 by considering an alternative benchmark model in the form of AIC-based iterative model.

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