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Effectiveness of monetary and macroprudential shocks on consumer credit growth and volatility in Turkey

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ABSTRACT

This paper proposes a panel VAR model to uncover the effect of monetary policy and macroprudential tightening probability on general purpose loans, housing loans, vehicle loans, credit cards and their respective volatilities in Turkey. To conduct our analysis, first, we compare a number of stochastic volatility models using our loan and credit card series in a formal Bayesian model comparison exercise, in order to determine the best volatility model for our series. Second we disclose the latent probability of macroprudential tightening from the binary information of policy episodes, using an instrumental variable probit model estimated by conditional maximum likelihood with heteroscedasticity robust standard errors. Lastly we estimate the dynamic impact of monetary policy and macroprudential measures using a panel VAR, incorporating the latent probability of tightening episodes, credit growth, industrial production growth, loan rates, inflation and credit growth volatilities into the endogenous system of equations. We conclude that macroprudential tightening is effective in dampening credit growth, credit growth volatility and reducing consumer price inflation. Besides, this effect is more prominent when macroprudential tools are administered in coordination with monetary policy.
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1. Introduction

After the global financial crisis macroprudential tools are seen as useful policies to reduce financial imbalances. The global crisis reminded us that financial stability has a macroprudential or systemic dimension that should not be ignored.[1] In addition to that, global crisis helps us understand the importance of global build-up of systemic-risk and financial imbalances whose sudden unfurling turned out to have severe global macroeconomic consequences. Recent global crisis also highlighted the need to go beyond microprudential approach to macro based financial regulation and supervision. The policy stance is concentrating notably on the usage, implementation and effectiveness of macroprudential tools as well as their impact on macroeconomic outcomes and their relationship with monetary policy.

The implementation of macroprudential policies for financial stability raises a number of challenges. One important challenge is that little is known about their effects as it is difficult to quantify the effectiveness of these measures, especially when macroprudential actions involve multitude of instruments. These instruments are taken at infrequent intervals and they are in use for a very short time span only making traditional regression analysis difficult. Accordingly, in the wake of the financial crisis, macroprudential policy has attracted considerable attention among researchers and policy makers and the literature on the usage, implementation and the effectiveness of macroprudential policies now is growing very fast.

Turkey faced rapid credit growth after the 2001 crisis, which was a local crisis, with recovering economic fundamentals afterwards. Institutions respond to this crisis with several structural reforms agenda that has fiscal, monetary and prudential dimensions. Rapid credit growth after 2001 crisis is accompanied with tight regulations and supervision within the banking system. In this respect, most of the prudential policies in Turkey are enforced through the banking system till 2011. For example, banks

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[1] See Galati and Moessner (2017), Cerutti et al. (2017) and Cakir (2017) for a conceptual framework of macroprudential design.

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were not allowed to have currency mismatches, foreign currency loans to consumers were prohibited, and there were restrictions on foreign currency lending to non-financial firms. Tight restrictions were introduced on distributing bank dividends, new bank entry and branch openings. During this regulatory period the Banking Regulation and Supervision Agency (BRSA) in Turkey enforced significantly higher minimum capital adequacy and liquidity coverage ratios than required by international standards. Against the high volatility in capital flows during the post-global crisis period, which materialized with the quantitative easing policies of advanced economies, Turkey has taken more steps towards implementing explicit macroprudential policies after 2011. Accordingly, the Central Bank of the Republic of Turkey (CBRT) reshaped the inflation targeting framework by incorporating financial stability as an additional objective.[2]

With this paper we aim to offer a mixture of methodologies to correctly measure the effects of monetary and macroprudential policies in Turkey especially on consumer credit market, i.e. credit growth and credit growth volatility. In this framework, first we start with estimating the volatility for credit data employing various stochastic volatility models. Second, we use binary macroprudential policy indicators, acknowledging their endogenous nature, i.e. a macroprudential tightening is an endogenous response to a previous heating in credit markets and we employ instrumental variable probit model to uncover the latent propensity to macroprudential tightening from the observed binary policy data. We estimate the instrumental variable probit model by conditional maximum likelihood with heteroscedasticity robust standard errors. Lastly, we apply panel VAR of Love and Zicchino (2006) to uncover the effect of monetary and macroprudential polices effectively used in Turkey.

The literature on the effectiveness of macroprudential policy tools is still in its infancy. In recent years, however, increasing efforts have been made to fill this gap. This paper complements other studies on the effectiveness of macroprudential policies. Different from the existing literature on the effects of macroprudential tools, our main contribution is analyzing this effect by exploiting the endogenous nature of these tools and analyzing the transmission from a possible shock to these polices to credit growth and credit growth volatility. This is the first study in the literature that discusses the importance of the effect of such policies on the second moment of credits.

The empirical literature on macroprudential policies has broadly followed two approaches in assessing the effects of macroprudential tools: reduced-form regression analysis conducted using cross country panel regressions and reduced-form regression analysis based on microdata.[3] Cross-country panel data studies can do a relatively good job of controlling for global and local factors, by including a host of global variables in the regressions as well as fixed effects to capture unobserved heterogeneity. Such control variables often include global variables, such as the VIX, and macroeconomic variables to control for local factors. The literature also makes use of information on various policy actions as an independent variable to explain asset price movements and credit growth in a time-series or dynamic panel regression framework.[4] Each method, i.e. reduced form regression analysis using cross-country panel regression or microdata has both advantages and disadvantages. However, it is important to address the main problem, that is the endogenous nature of the macroprudential policies.

A key issue in both the academic literature and the policy debate is how the macroprudential policy interacts with monetary policy, i.e. should monetary policy be regarded as a complement or even a substitute for macroprudential policy for restraining a potential credit boom? Both the theoretical literature and the empirical literature gives different answers to this question. Yet, most of the papers offer an optimal cooperation between two sets of instruments. Collard et al. (2017) and Svensson (2017) claim that the optimal monetary policy alone is not efficient enough for financial instability and illustrates the optimal conditions for the complementarity conditions of monetary and macroprudential policies together to serve as the first line of defense against financial instability. Brunnermeier and Sannikov (2016) show that welfare is significantly improved by a combination of macroprudential policy and monetary policy. Within this framework our results highlight that - using information for consumer loans over the period of 2006–2017 monetary policy and macroprudential policy are complements and the existence of macroprudential policies besides monetary policy increases the effectiveness of these tools. We manifest these results for the consumer credit market, i.e. credit cards, general purpose loans, housing loans and vehicle loans.

The results should be interpreted with the following interpretations in mind. First limitation is related to the tightening periods related to the macroprudential policies. The policy measure used for the estimations reflect the direction of the policy action, but not the strength of the action. When we estimate the macroprudential tightening probability, we use a binary variable for the tightening periods and for certain periods more than one policy action is taken or for some other periods the intensity of the action taken is higher than the other periods in question, which might cause some measurement errors. Measurement error related to the intensity of the macroprudential policy actions are commonly mentioned in the literature, therefore one must be wary of the binding effect of this measurement error which is likely to weaken the estimated effect of macroprudential policies.[5] A second limitation is related to the difficulty in completely encountering the potential endogeneity of macroprudential policies. To alleviate such concerns we use a probit model with instrumental variables to extract the macroprudential tightening probability and a GMM estimation within panel VAR, which employs additional dynamic instruments in the empirical framework.

Our paper is related to a large body of literature on the effectiveness of macroprudential tools, but there are few papers that are particularly related to this study. Tillmann (2015) proposes a VAR augmented by qualitative variables (Qual VAR) to estimate the effects macroprudential tightening on the housing market of Korea and conclude that macroprudential tightening is effective in dampening credit growth and reducing the appreciation of house prices. Tovar Mora et al. (2012) examine the role of reserve requirements and other macroprudential instruments with cross-country evidence on how they influence real private bank credit growth and their results show that these instruments have a moderate and transitory effect and play a complementary role to monetary policy. Greenwood-Nimmo and Tarassow (2016) examine the implications of monetary shocks and macroprudential shocks for aggregate financial fragility using a sign restricted VAR with US data and they suggest that combined

[2] Kara (2016a) and Kara (2016b) for detailed information about Turkey's experience with macroprudential polices.

[3] See Aiyar et al. (2014), Akinci and Olmstead-Rumsey (2018), Erdem et al. (2017), Fendoğlu (2017), Bruno et al. (2017), Jiménez et al. (2017), Dell'Ariccia et al. (2017) and Altunbas et al. (2018).

[4] See Lim, Costa, Columba, Kongsamut, Otani, Saiyid, Wezel, and Wu (Lim et al.), Galati and Moessner (2013), Claessens (2015),Cerutti et al. (2017) and Kahou and Lehar (2017) for an overview and the use of macroprudential policies.

[5] See Fendoğlu (2017) for a similar argument.

monetary and macroprudential approach is more effective for financial stability. Lastly Gambacorta and Murcia (2017) evaluate the effectiveness of macroprudential tools and their interaction with monetary policy for five Latin American countries and they propose that macroprudential tools have a greater effect on credit growth when reinforced by the use of monetary policy to push in the same direction.

Similar to all Tillmann (2015), Tovar Mora et al. (2012), Greenwood-Nimmo and Tarassow (2016) and Gambacorta and Murcia (2017), this paper also examines whether macroprudential policy tools are effective besides monetary policy for restraining consumer credit growth yet our paper differs from the literature in two fundamental ways. First, we try to measure the effectiveness of both the monetary policy shocks and macroprudential tightening shocks on not only credit growth but also on credit growth volatility. It is common to measure the impact of macroprudential tools on credit growth and house prices but not on credit growth volatility, which is very important for financial stability and in this respect, it is one of the few papers to measure this impact. Using capital requirements as a macroprudential policy tool Aguirre and Blanco (2015) find that macroprudential policy smooths output, price, interest rate and credit volatility over the business cycle.[6] Second, we combine the "Qual VAR" and the "Panel VAR" methodology to measure the latent probability of macroprudential tightening as the first step via instrumental variable probit model, and then we use this probability within the Panel VAR in the second step. In this way, we try to encounter the endogeneity problem related to the macroprudential policy shocks.[7]

The remainder of this paper is organized as follows. Section 2 provides information on the data employed in this study. This section also discusses various methodologies employed in this paper, i.e. stochastic volatility models to extract the volatility of loan data, instrumental variable probit method to extract the latent probability of macroprudential tightening and lastly panel VAR to measure the impact of macroprudential shocks. Section 3 provides the empirical results of the panel VAR, policy implications and some robustness exercises. Section 4 concludes.

2. Data and methodology

Our loan-level data, i.e. loans to households by banks and the interest rates related to those loans come from the CBRT Electronic Data Delivery System.[8]

We use three different types of loans, i.e. general purpose loans, housing loans, vehicle loans and credit cards. This data set has weekly frequency. We use weekly frequency data to extract the credit growth volatilities and then convert weekly volatilities to monthly frequency to use them in IV probit and Panel VAR.

Weighted average funding rate (WAFR) is used as the monetary policy rate. However, since this data started to be reported in 2011, the Istanbul Stock Exchange (BIST) interbank overnight borrowing rate was used as a proxy for previous periods. WAFR come from the CBRT Electronic Data Delivery System and we use Bloomberg for BIST interbank overnight borrowing rate. Seasonally adjusted industrial production index and consumer price index comes from the Turkstat. We use TRAMO-SEATS to seasonally adjust consumer price index. The source of VIX is Bloomberg.

To define macroprudential tightening we employ a dummy variable, which are designed to take the value of one for periods when strict macroprudential policies are implemented and zero otherwise. We decide on the macroprudential tightening periods using Cerutti et al. (2015), Fendoğlu (2017) and Eroğlu (2018).[9] It is important to state that we exclude all the macroprudential policy actions that are related to commercial credits, as those types of credits are beyond the scope of this study. We use only those instruments that directly address the consumer loans of the households. Table (1) illustrates the descriptive statistics of the data used in this paper.

2.1. Modelling time-varying volatility

The effect of monetary policy and macroprudential policy on credit growth volatility is a largely unexplored area. Mishkin and Schmidt-Hebbel (2007) state that, when the monetary policy is suboptimal, the economy will exhibit large output and inflation volatility and will be located at a significant distance from the frontier. A similar result will be observed given a suboptimal macroprudential policy which will create credit growth volatility that will result in output volatility, especially in a developing emerging market country which depends on credits to grow. Indeed, Gould et al. (2016) employ credit volatility as a financial stability indicator and find that countries with higher volatility of credit tend to have lower growth rates. Bennani et al. (2017) state that the reduction in credit volatility is viewed as a proxy for reducing the welfare cost of fluctuations within a dynamic stochastic general equilibrium (DSGE) model. Accordingly, credit volatility enters DSGE as an objective function (ad hoc credit volatility function) that needs to be minimized to smooth financial cycles.[10]

We assess the credit growth volatility using stochastic volatility models, where the volatility is a latent variable that follows a stochastic process.[11] We choose the best stochastic volatility model for out credit data out of seven different models, performing a formal Bayesian model comparison exercise given the data. For each seven volatility model, we compute the marginal data density, which evaluates how likely it is for the observed data to have occurred given the model. Using this measure we can obtain the posterior probabilities of the models.[12] We compare these seven time-varying volatility models against each other and choose the one that is better modelled as a latent stochastic process.

The first model is the standard stochastic volatility (SV) model:

$$y_t = \mu + \sigma_t, \quad \sigma_t \sim \mathcal{N}\left(0, e^{h_t}\right), \tag{1}$$

$$h_t = \mu_h + \phi_h(h_{t-1} - \mu_h) + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}\left(0, \omega_h^2\right). \tag{2}$$

where the log-volatility h_t follows a stationary $AR(1)$ process with $|\phi_h| < 1$ and unconditional mean μ_h.

The second stochastic volatility (SV-2) model has the same observation equation as in Eq. (1), but the log-volatility h_t follows a

[6] See Grydaki and Bezemer (2013) on the importance of lower credit volatility.

[7] Qual VAR methodology comes with its own problems. El-Shagi and von Schweinitz (2016) discuss the identification problem that is related to the procedure.

[8] https://evds2.tcmb.gov.tr/index.php?/evds/serieMarket.

[9] See Table (A1) in the Appendix, which provides a summary of macroprudential policy actions (tightenings) and how they are defined.

[10] In Bennani et al. (2017), macroprudential authority to minimize the loss function given by: $\phi_v = \arg\min\{\sigma^2_{creditgrowth} + \lambda_y \sigma^2_{GDPgrowth} + \lambda_v \sigma_v^2\}$, where σ_x^2 denotes the unconditional variance of variable x and the parameters λ_y, λ_v, reflect the policymaker's priorities when trading off a reduction in credit and GDP volatility and a variation in the instrument of an acceptable magnitude. ϕ_v is calibrated like a Basel III-type capital buffer rule.

[11] The results are generated by MATLAB codes provided by Chan and Grant (2016).

[12] See Koop (2003) for a detailed discussion on Bayesian model comparison.

Table 1
Panel summary statistics (2005-December to 2017-December).

Variable	ΔIP	ΔPR	$Pr-MaP$	ΔLR	ΔCRD	ΔCPI	$CRD-VOL$	ΔVIX
Credit cards								
mean	0.003	−0.009	0.339	−0.239	0.011	0.007	1.208	0.000
median	0.003	0.000	0.299	−0.041	0.011	0.007	1.207	−0.016
s.d.	0.021	0.678	0.269	1.940	0.017	0.005	0.038	0.211
max.	0.085	2.860	1.000	12.507	0.065	0.025	1.337	0.853
min.	−0.075	−2.340	0.000	−8.397	−0.036	−0.007	1.145	−0.486
General purpose								
mean	0.003	−0.009	0.384	−0.016	0.021	0.007	0.495	0.000
median	0.003	0.000	0.365	−0.095	0.017	0.007	0.429	−0.016
s.d.	0.021	0.678	0.240	0.924	0.018	0.005	0.167	0.211
max.	0.085	2.860	0.999	5.490	0.119	0.025	1.088	0.853
min.	−0.075	−2.340	0.005	−2.790	−0.012	−0.007	0.302	−0.486
Housing								
mean	0.003	−0.009	0.274	−0.015	0.018	0.007	0.269	0.000
median	0.003	0.000	0.209	−0.135	0.015	0.007	0.218	−0.016
s.d.	0.021	0.678	0.254	0.786	0.018	0.005	0.194	0.211
max.	0.085	2.860	0.999	3.890	0.119	0.025	1.334	0.853
min.	−0.075	−2.340	0.000	−3.330	−0.014	−0.007	0.147	−0.486
Vehicle								
mean	0.003	−0.009	0.291	−0.021	0.000	0.007	0.290	0.000
median	0.003	0.000	0.254	−0.115	−0.002	0.007	0.288	−0.016
s.d.	0.021	0.678	0.221	0.932	0.021	0.005	0.043	0.211
max.	0.085	2.860	0.999	5.350	0.113	0.025	0.450	0.853
min.	−0.075	−2.340	0.000	−1.920	−0.048	−0.007	0.171	−0.486

Definitions: ΔIP is the monthly logarithmic difference of seasonally adjusted industrial production index. ΔPR is the monthly difference of policy rate. $Pr-MaP$ is the macroprudential tightening probability. ΔLR is the monthly difference of consumer loan rates. ΔCRD is the monthly logarithmic difference of consumer loans. ΔCPI is the monthly logarithmic difference of seasonally adjusted consumer price index. $CRD-VOL$ is the volatility of consumer loans. ΔVIX is the monthly logarithmic difference of VIX.

stationary $AR(2)$ process:

$$h_t = \mu_h + \phi_h(h_{t-1} - \mu_h) + \rho_h(h_{t-2} - \mu_h)\varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}\left(0, \omega_h^2\right).$$

SV-2 model reduces to the standard SV model when $\rho_h = 0$.

The third stochastic volatility model allows for the possibility of infrequent jumps, which can accommodate drastic changes in credit growth. Under the stochastic volatility model with jumps (SV-J), the observation equation becomes:

$$y_t = \mu + k_t q_t + \sigma_t, \quad \sigma_t \sim \mathcal{N}\left(0, e^{h_t}\right),$$

where the log-volatility h_t follows a stationary $AR(1)$ process. $q_t \in 0, 1$ is a jump variable with success probability $P(q_t = 1) = \kappa$. Hence, if $q_t = 1$, a jump occurs at time t and its size is determined by if k_t, which is modelled as $k_t \sim N(\mu_k, \nu_k^2)$.

Next we examine the stochastic volatility in mean (SV-M) model of Koopman and Hol Uspensky (2002), under which the stochastic volatility enters the observation equation as a covariate:

$$y_t = \mu + \lambda e^{h_t} + \sigma_t, \quad \sigma_t \sim \mathcal{N}\left(0, e^{h_t}\right),$$

As before, the log volatility follows a stationary $AR(1)$ process as in Eq. (2). The parameter λ captures the extent of volatility feedback. SV-M model reduces to the standard SV model when $\lambda = 0$.

The fifth model is a version of the stochastic volatility models with moving average innovations (SV-MA) in Chan (2013). The first order SV-MA model will be:

$$y_t = \mu + \sigma_t,$$

$$\sigma_t = u_t + \psi u_{t-1}, \quad u_t \sim \mathcal{N}\left(0, e^{h_t}\right).$$

where $u_0 = 0$ and $|\psi| < 1$ and the log volatility follows a stationary $AR(1)$ process as in Eq. (2).

The sixth model is the stochastic volatility model with t innovations (SV-t):

$$y_t = \mu + \sigma_t, \quad \sigma_t \sim t_\nu\left(0, e^{h_t}\right).$$

where the log-volatility follows a stationary $AR(1)$ process as in Eq. (2).

The last model is the stochastic volatility model with leverage (SV-L), which allows a leverage effect. Specifically, the innovations in the observation and state equations can potentially be correlated:

$$y_t = \mu + \sigma_t, \quad \sigma_t \sim \mathcal{N}\left(0, e^{h_t}\right),$$

$$h_{t+1} = \mu_h + \phi_h(h_t - \mu_h) + \varepsilon_t,$$

where the innovations σ_t and ε_t jointly follow a bivariate normal distribution:

$$\begin{pmatrix} \sigma_t \\ \varepsilon_t \end{pmatrix} \sim \mathcal{N}\left(0, \begin{pmatrix} e^{h_t} & \rho e^{\frac{1}{2}h_t}\omega_h \\ \rho e^{\frac{1}{2}h_t}\omega_h & \omega_h^2 \end{pmatrix}\right)$$

where, if $\rho < 0$, given a negative shock to y_t at time t, the volatility at time $t+1$ tends to be larger. It is also clear that when $\rho = 0$, this model reduces to the standard SV.

All the seven stochastic volatility models are estimated using Bayesian techniques; Markov Chain Monte Carlo (MCMC) methods.[13] We sample from the posterior distributions of the models by constructing Markov samplers and use the posterior draws obtained to compute various quantities of interest. For the stochastic volatility models, log-volatilities are sampled jointly

[13] See the Appendix for prior Definitions and hyperparameters.

Table 2
Log marginal likelihoods of the SV models.

	Credit cards	General purpose	Housing	Vehicle
SV	−1052.7	−490.1	−107.4	−481.7
	(0.00)	(0.01)	(0.03)	(0.01)
SV-2	−1047.1	−490.5	−110.1	−480.9
	(0.00)	(0.14)	(0.06)	(0.02)
SV-J	−1055.9	−495.1	−112.9	−485.3
	(0.09)	(0.10)	(0.06)	(0.34)
SV-M	−1056.6	−456.2	−61.7	−357.0
	(0.02)	(0.03)	(0.02)	(0.04)
SV-MA	−1013.0	−493.1	−39.6	−434.5
	(0.00)	(0.01)	(0.02)	(0.01)
SV-*t*	−1054.4	−491.3	−108.7	−482.0
	(0.01)	(0.02)	(0.02)	(0.02)
SV-L	−1052.7	−491.0	−107.6	−482.1
	(0.01)	(0.02)	(0.07)	(0.01)

Note: The numerical standard errors are in parantheses.

using acceptance-rejection Metropolis-Hastings described in Chan (2017).[14] The marginal likelihoods for the stochastic volatility models are computed using the adaptive importance sampling approach in Chan and Eisenstat (2015).

To choose the best volatility model for the credit growth we use Bayesian model comparison via the Bayes factor and the Bayes factor in favour of M_i against M_j is defined as:

$$BF_{ij} = \frac{p(y|M_i)}{p(y|M_j)},$$

where

$$p(y|M_k) = \int p(y|\theta_k, M_k)p(\theta_k|M_k)d\theta_k$$

is the marginal likelihood under model $M_k, k = i,j$, $p(y|\theta_k, M_k)$ being the likelihood function that depends on the model specific parameter vector θ_k of dimension p_k and a prior density $p(\theta_k|M_k)$. This marginal likelihood can be interpreted as a density forecast of the data under model M_k evaluated at the actual observed data y. Since the Bayes factor BF_{ij} is simply a ratio of two marginal likelihoods, researchers often only report the marginal likelihoods of the set of competing models and we choose to do so in this paper.[15]

The results of the marginal likelihoods for seven SV models estimated for credit cards, general purpose loans, housing loans and vehicle loans are reported in Table (2). The data frequency is weekly and the sample period is from December 2005 to December 2017. The data are transformed into rates of change by taking the first difference of the logs. We estimate the GARCH counterparts of these SV models but for all series they perform considerably worse than these models therefore we choose not to report them in the paper. Under GARCH models the conditional variance is a deterministic function of the parameters and past data in contrast to SV models, in which the log-volatility is a random variable. Therefore, SV models are more robust to misspecification and to drastic changes in the time series. This helps explain why SV models perform much better then their counterpart GARCH models. Table (2) shows that the best model is either SV-MA or SV-M for credit growth series and credit cards. The Bayes factors for the four series clearly favour of either SV-MA or SV-M models for these series.[16] Figure (1) exhibits the volatility series of credit cards, general purpose, housing and vehicle loans. We will use these volatilities later within a panel VAR to observe whether monetary policy and macroprudential shocks are able to affect them significantly.

2.2. Modelling latent macroprudential policy probability

There is no continuous indicator of macroprudential policy actions. What do we have at hand are a few tightening or easing episodes of macroprudential policy. Including a binary endogenous variable into a panel VAR, i.e. a linear probability model will unfortunately produce results that are difficult to interpret. Therefore, we uncover the latent probability of macroprudential tightening from the binary information of policy episodes, using an instrumental variable probit model estimated by conditional maximum likelihood with heteroscedasticity robust standard errors. In order to account for the endogeneity of macroprudential shocks, the probit function for the tightening outcome is simultaneously estimated with the dynamic interaction with other variables that are assumed to be endogenous to policy actions.[17] We thus specify the following model:

$$y_t^* = Z_t\beta + X'_t\gamma + \varepsilon_t$$

where y_t^* is a latent variable for unobservable propensity for macroprudential tightening. We only observe a binary dependent variable $y_t \in 0, 1$, which is driven by a continuous latent variable y^*. γ is defined so that $cov(\varepsilon_t, X_t) = 0$. Z_t is potentially endogenous and thus correlated with ε_t. We define an instrument W_t which does not influence y_t^* directly but is correlated with Z_t. In our case

$$Z_{t-s} = \Delta IP_{t-s}, \Delta PR_{t-s}, Pr - Map_{t-s}, \Delta LR_{t-s}, \Delta CRD_{t-s}, \Delta CPI_{t-s}, \Delta LR_{t-s}, CRD - VOL_{t-s} \quad \text{for } s = 0, 1 \quad \text{and}$$
$$W_{t-s} = \Delta IP_{t-s}, \Delta PR_{t-s}, Pr - Map_{t-s}, \Delta LR_{t-s}, \Delta CRD_{t-s}, \Delta CPI_{t-s}, \Delta LR_{t-s}, CRD - VOL_{t-s} \quad \text{for } s > 1.$$

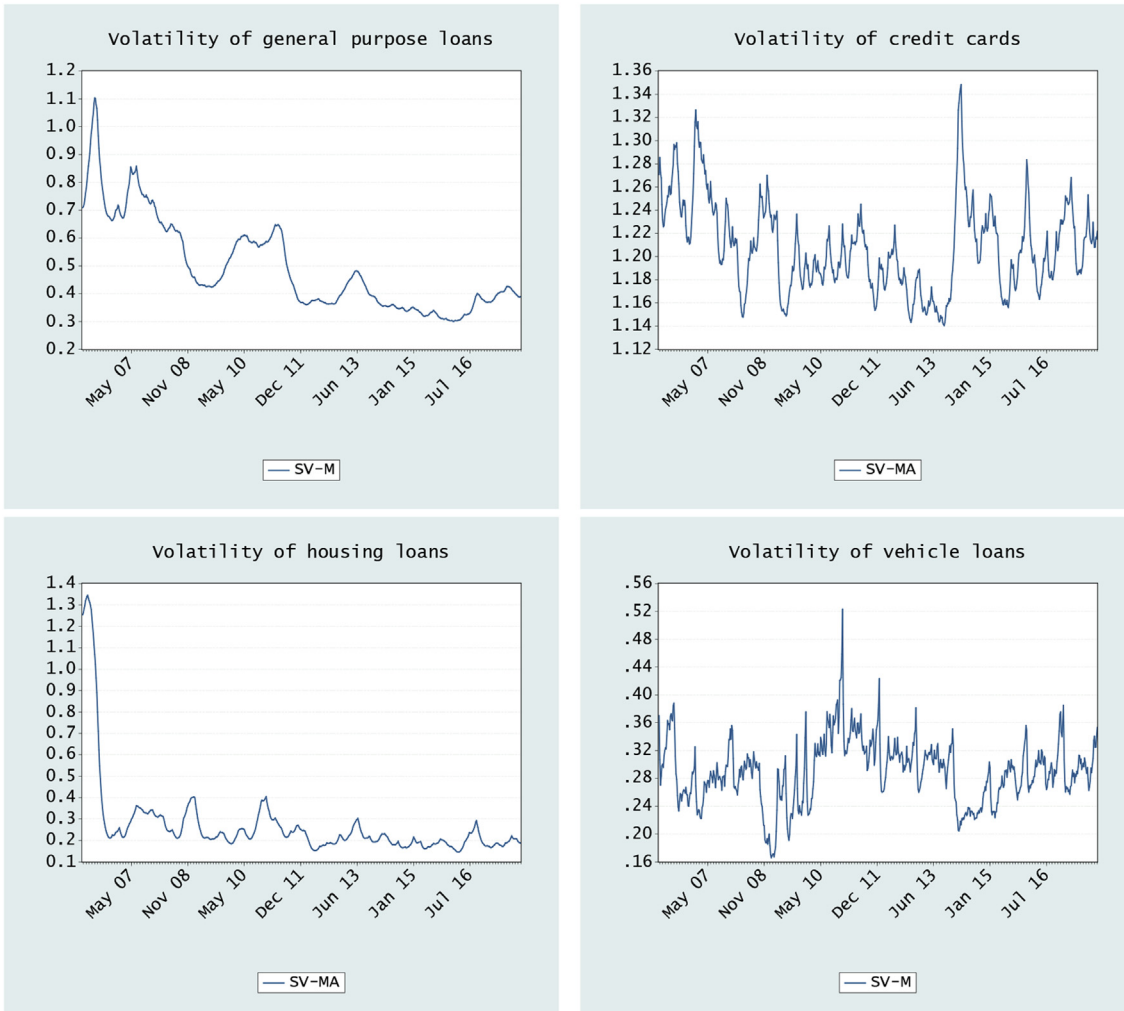
Table (3) presents the results from the IV probit regressions for each of the four series. To save some space we only list the results related to two variables, i.e., credit growth ΔCRD and credit growth volatility $CRD - VOL$. We expect a negative sign for credit growth and credit growth volatility, and as can be observed from Table (3), for most of the regression results we get correct signs. To begin with, the Wald test of exogeneity provides evidence that

[14] See Chan and Grant (2016) for more details.

[15] The computation of the marginal likelihood is non-trivial as it is often high dimensional and therefore cannot be obtained analytically. That is why the marginal likelihoods for the stochastic volatility models are computed using the adaptive importance sampling approach in Chan and Eisenstat (2015).

[16] The posterior estimates of the model parameters for the SV models are illustrated by Tables (A2), (A3), (A4) and (A5) in the Appendix.

[17] See Wooldridge (2010). The model is estimated using ivprobit in Stata.



Note: SV-M represents stochastic volatility in mean. SV-MA represents stochastic volatility model with moving average innovation.

Fig. 1. Graphs of stochastic volatility models.

Table 3
IV Probit results.

	Credit cards	General purpose	Housing	Vehicle
Coefficient of Credit Growth	−3.903	5.039	−1.569	−81.569***
Marginal Effects (SE)	(5.520)	(11.861)	4.645027	(31.639)
Coefficient of Credit Growth Volatility	−2.237	−0.286	0.283	34.559***
Marginal Effects (SE)	(2.603)	(1.008)	(0.816)	(13.219)
Instrument Significance# $\chi^2_{[df]}$	164.26 [10]	220.05 [10]	12.30 [10]	5.54 [10]
(p-value)	(0.000)	(0.000)	(0.031)	(0.853)
Over-identification test $\chi^2_{[df]}$	5.45 [10]	2.31 [10]	0.74 [10]	6.34 [10]
(p-value)	(0.859)	(0.804)	(0.946)	(0.786)
% of Correct Classification	88.19	95.35	97.67	90.48

Note: # Amemiya-Lee-Newey minimum χ^2 statistic. Marginal effects are estimated holding model covariates at their means. Standard errors (SE) of marginal effects are listed in parentheses. The Chi-square test statistics (χ^2) and their degrees of freedom [df] for testing the joint significance of the instruments and for testing the appropriateness of the over-identification restrictions of the instruments are reported. *** refers to 1% significance level.

macroprudential tightening is, indeed an endogenous variable.[18] The validity of the instruments was tested using the Amemiya-Lee-Newey over identification test.[19]

One measure of how well probit models fit the data is to consider the number of correct predictions or classifications that they generate. The approach here is to predict individual's scoring on 1 on the dependent variable "y", i.e. in our case it is macroprudential tightening", based on his or her predicted probability. A common cutoff for the predicted probability is 0.5 so that:

$$\widehat{y} = 1 \quad \text{if } \widehat{\pi} > 0.5$$

$$\widehat{y} = 0 \quad \text{if } \widehat{\pi} \leq 0.5$$

where $\widehat{y}$ is the predicted score on the response variable. Whenever there is agreement between $\widehat{y}$ and y, there is correct prediction. The higher the percentage of correctly classified observations, the better the model fit is. We can observe from the last row of Table (3) that the correct classification rate is very high for all the loan categories which illustrates that the IV-probit gives us good predictions with respect to the probability of macroprudential tightening.

2.3. Panel data VAR

The panel data VAR methodology combines the traditional VAR approach, which treats all the variables in the system as endogenous, and employs panel data with a VAR that also allows for unobserved individual heterogeneity. In its general form, a panel data VAR model can be written as follows:

$$Y_{it} = \Gamma_0 + \Gamma_1 Y_{it-1} + f_t + d_t + e_{it} \tag{3}$$

where Y_{it} is a vector of seven key variables: ΔIP that is the industrial production growth (log-difference of seasonally adjusted industrial production index), ΔPR that is the log-difference of policy rate, ΔLR that is the log-difference of general purpose, housing, vehicle loan and credit card rates, ΔCRD that is the credit growth rate (log-difference of general purpose, housing, vehicle loans and credit cards), ΔCPI that is the log-difference of consumer price index, $CRD - VOL$ that is the volatility of general purpose, housing, vehicle loans and credit card growth rates and $Pr - MaP$, i.e. probability of a macroprudential tightening for general purpose, housing, vehicle loans and credit cards.[20]

The advantage of the panel VAR is the same as the advantage of any panel approach, i.e., in allowing for explicit inclusion of a fixed effects in the model, denoted f_i in Eq. (3), which captures all unobservable time-invariant factors at a loan-type level. This is important for our purposes as inclusion of these fixed effects allows each loan category to have a loan specific level of each of these factors in the model. However, inclusion of these fixed effects presents an estimation challenge that arises in any dynamic model including lags of the dependent variable: the fixed effects are correlated with the regressors and, therefore, the mean-differencing procedure commonly used to eliminate fixed effects would create biased coefficients. To avoid this problem we use forward mean-differencing, which is a very common procedure in panel VAR literature, also referred to as the "Helmert procedure".[21] This procedure removes only the forward-mean, i.e., the mean of all the future observations available for each loan-month. This transformation preserves the orthogonality between transformed variables and lagged regressors, which allows us to use lagged regressors as instruments and estimate the coefficients by system GMM.[22] To deal with the time effects, we time difference all the variables prior to inclusion in the model, which is equivalent to putting time dummies in the system.

Model represented by Eq. (3) is commonly referred to as reduced form, which contains lagged values of all other variables in the system. The prime benefit of the VAR system is in allowing one to evaluate the impact of the orthogonal shocks, which is accomplished with the impulse response functions. Since, the actual variance-covariance matrix of the errors is unlikely to be diagonal, to isolate shocks to one of the variables in the system it is necessary to decompose the residuals in such a way that they become orthogonal. The usual convention is to adopt a particular ordering and allocate any correlation between the residuals of any two elements to the variable that comes first in the ordering. This procedure is known as Cholesky decomposition of the variance-covariance matrix of residuals and is equivalent to transforming the system in a recursive VAR for identification purposes.[23]

The identification assumption via recursive ordering assumes that the variables which come earlier in the ordering affect all the following variables contemporaneously, while the variables that come later affect the previous variables only with a lag. Accordingly, we employ the following ordering: $\Delta IP \rightarrow \Delta PR \rightarrow Pr - MaP \rightarrow \Delta LR \rightarrow \Delta CRD \rightarrow \Delta CPI \rightarrow CRD - VOL$. ΔIP is placed at the very beginning of the ordering because the state of the real economy is expected to affect many, if not all, other variables contemporaneously, but be affected by other variables in the model with a lag. Indeed, the phase of the business cycle in any given period affects all the other variables, and ΔIP serves a s a proxy for the state of the business cycle. Given the state of the economy, which is represented by ΔIP, the authorities can change the policy rate ΔPR and the macroprudential policies $Pr - MaP$. These policy variables can respond to changes in ΔIP quickly, but will only be expected to affect the real state of the economy with a lag as it takes time for the monetary policy response. It is expected that the policy rate is transmitted to loan rates which in turn will affect the credit growth and volatility, therefore we put these variables last.

For the analysis of the impulse response functions, we need an estimate of their confidence intervals and we generate the confidence intervals for the impulse responses using Monte Carlo simulations. In addition, we evaluate variance decompositions, which show the percent of variation in one variable that is explained by the shock to another variable, accumulated over time. We report the total effect accumulated over the 10 months, but longer time horizons produced equivalent results.

3. Empirical results

This section discusses the simulations of impulse responses, which are represented by Figures (2)–(4).[24] In these figures, we plot the responses of variables to a one-standard deviation shock to

[18] The Wald test of exogeneity tests whether the correlation between the errors in the full probit equation and reduced-form equation for the endogenous regressor, macroprudential tightening, is equal to zero. Accepting the null hypothesis would have meant that the suspected endogenous variable is in fact exogenous and, therefore, a normal probit could be used.

[19] It tests the joint null hypothesis that the excluded instruments are uncorrelated with the error term (and therefore are valid instruments). See Baum et al. (2016).

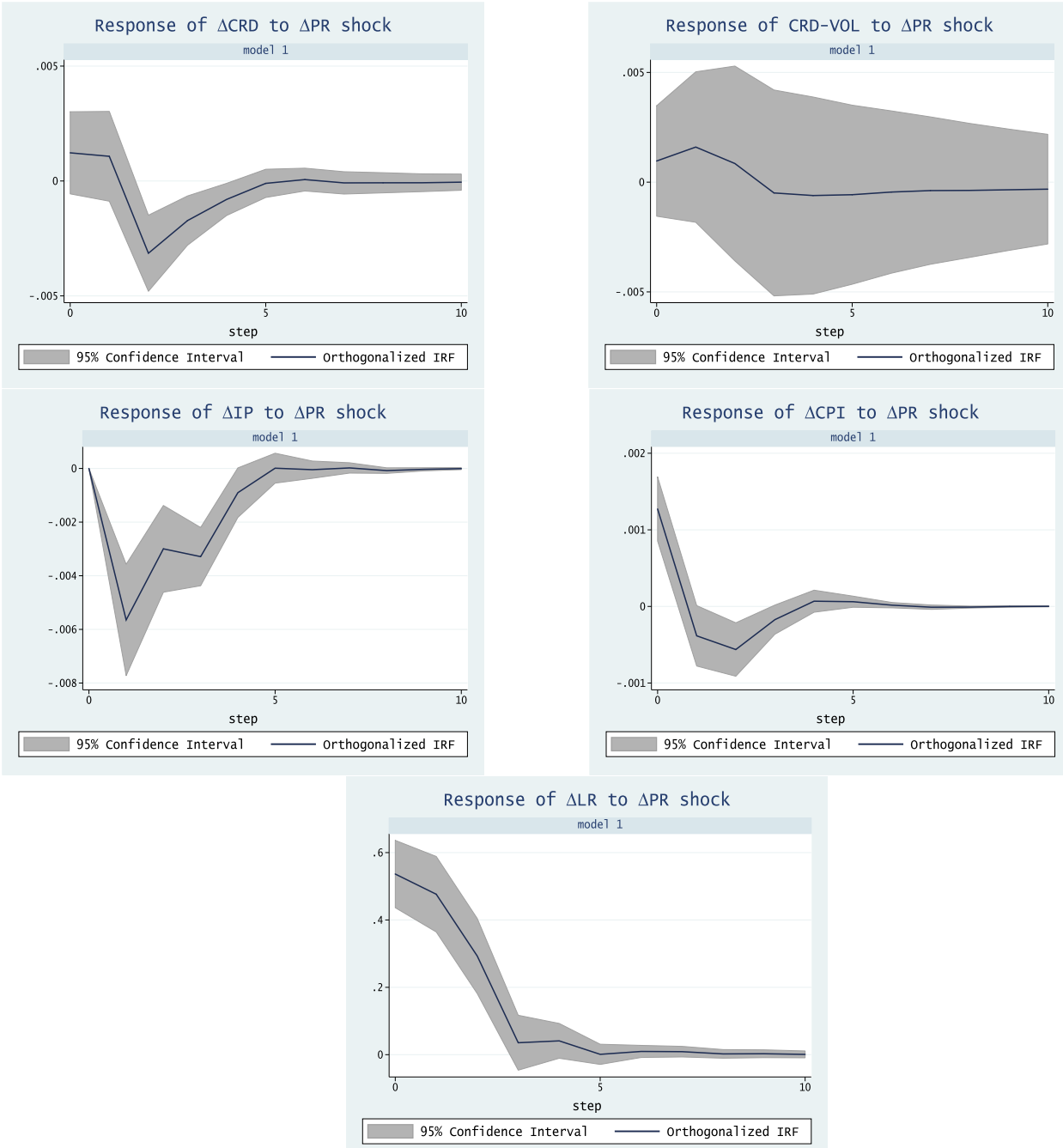
[20] A global risk aversion variable proxied by the VIX index is included as an exogenous variable.

[21] See Arellano and Bover (1995) for details.

[22] Our panel VAR estimation routine follows Love and Zicchino (2006).

[23] See Hamilton (1994) for details.

[24] The coefficient estimates and standard errors are given by Table (A6) and Table (A7) in the Appendix.

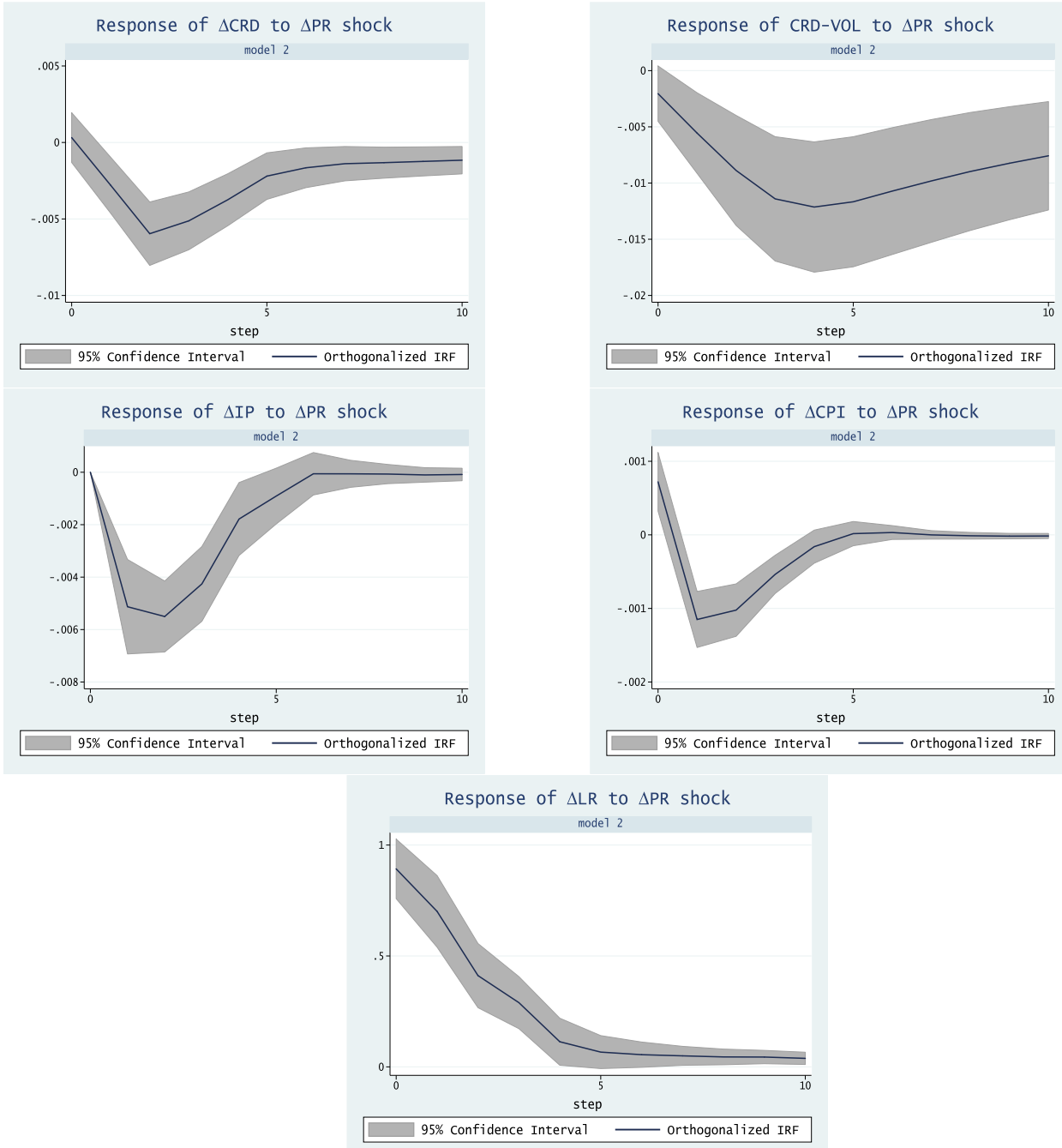


Note: ΔIP is the monthly logarithmic difference of seasonally adjusted industrial production index. ΔPR is the monthly difference of policy rate. ΔLR is the monthly difference of consumer loan rates. ΔCRD is the monthly logarithmic difference of consumer loans. ΔCPI is the monthly logarithmic difference of seasonally adjusted consumer price index. $CRD - VOL$ is the volatility of consumer loans.

Fig. 2. Impulse responses for 1 lag VAR of monetary policy shock (Model 1/no macroprudential policy).

the monetary policy and macroprudential policy variables. All graphs show responses for the first 10 months, and nearly all of the responses converge to zero in this time frame. The two lines on either side of the impulse response are 5th and 95th percentile bounds constructed using Monte Carlo simulations with 1000 repetitions. Thus, for the periods where the zero line is outside of the error bands we can be 95 percent certain that there is indeed a non-zero effect on the variable under consideration.

Figure (2) is based on our panel VAR model (model 1) that does not include the macroprudential tightening probability variable $Pr - MaP$: $\Delta IP \rightarrow \Delta PR \rightarrow \Delta LR \rightarrow \Delta CRD \rightarrow \Delta CPI \rightarrow CRD - VOL$. ΔIP. First, we will discuss the responses of credit growth and credit growth volatility to monetary policy shocks. It is clear from Figure (2) that monetary policy shock has a negative and significant impact on both credit growth and volatility. The sign of both of the responses is expected, i.e. an increase in policy rate will result in a decreasing credit growth rate and volatility. Second, the response of industrial production growth is significant, negative and very close to the response of credit growth, which is an expected falling industrial outcome of the contractionary monetary policy. Inflation also falls in response to production growth. Finally, it is not surprising to observe a significant hike in the loan rates after a contractionary



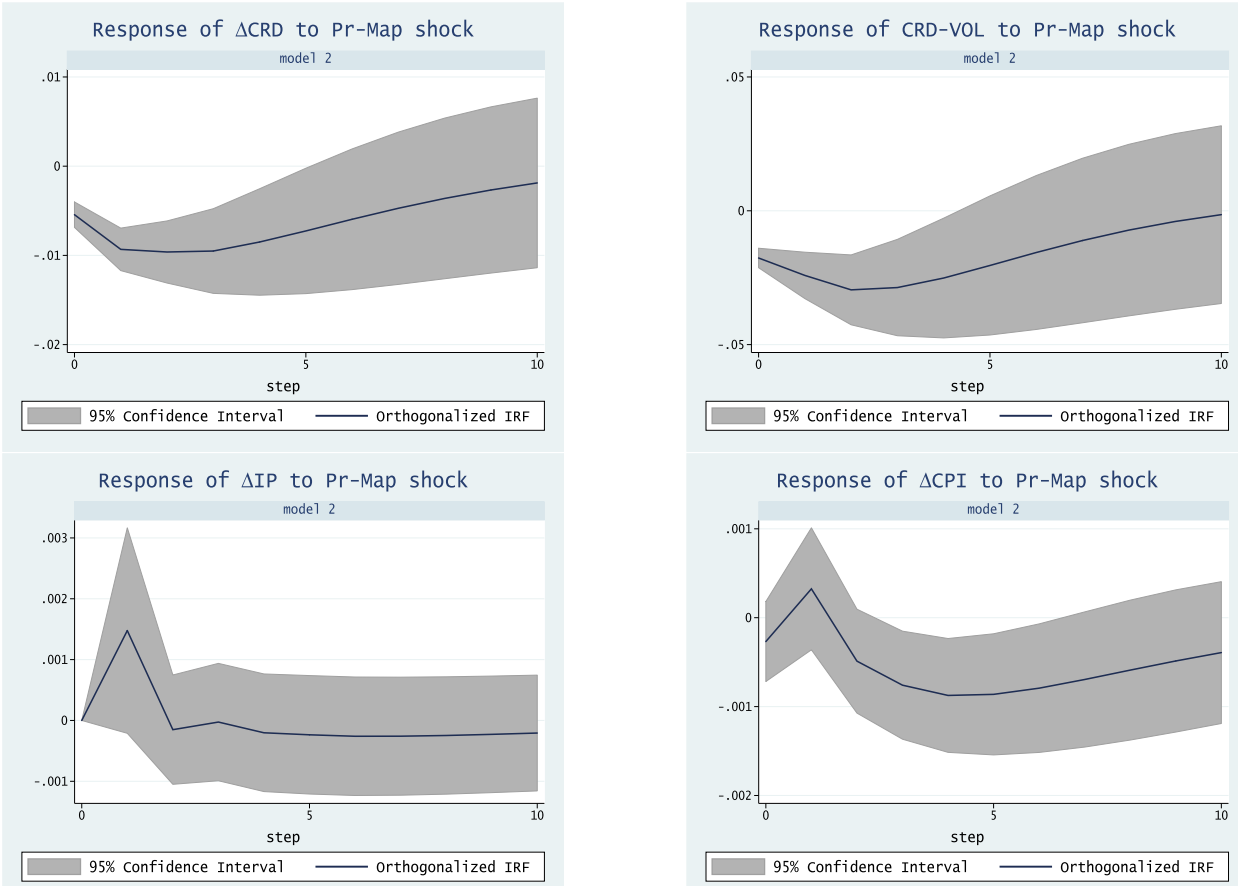
Note: ΔIP is the monthly logarithmic difference of seasonally adjusted industrial production index. ΔPR is the monthly difference of policy rate. ΔLR is the monthly difference of consumer loan rates. ΔCRD is the monthly logarithmic difference of consumer loans. ΔCPI is the monthly logarithmic difference of seasonally adjusted consumer price index. $CRD - VOL$ is the volatility of consumer loans.

Fig. 3. Impulse responses for 1 lag VAR of monetary policy shock (Model 2/with macroprudential policy).

monetary policy.

Focusing next on the responses of the same variables to monetary policy shocks when we include macroprudential tightening probability into the system (model 2), Figure (3) illustrates that the sign of the responses do not change, they are all significant and stronger than the responses that we get from model 1.[25] This result is very intuitive, as macroprudential tools are designed to address financial stability concerns in response to credit growth rates. As Figure (3) shows an increase in policy rates with macroprudential tightening causes an expected decrease in credit growth at the expense of decreasing industrial production. Slowing growth of the economy also causes inflation to decline. Most important to the purpose of this paper is the response of credit growth volatility to a monetary policy shock and macroprudential shock. Other than the response of industrial production growth, we observe similar responses as before, i.e. a significant decline in credit growth and credit growth volatility. Yet, as Figure (3) illustrates that the response of credit growth volatility to monetary policy shocks are significant. This result is in line with our expectations as we observe similar responses of credit growth to monetary policy shock with/without macroprudential policy, yet without macroprudential policy we cannot observe significant responses for volatility. If we

[25] We decide on the lag order $p=1$ of panel VAR using Akaike and Bayesian Information Criteria.



Note: ΔIP is the monthly logarithmic difference of seasonally adjusted industrial production index. $Pr - MaP$ is the macroprudential tightening probability. ΔCRD is the monthly logarithmic difference of consumer loans. ΔCPI is the monthly logarithmic difference of seasonally adjusted consumer price index. $CRD - VOL$ is the volatility of consumer loans.

Fig. 4. Impulse responses for 1 lag VAR of macroprudential policy shock (Model 2/with macroprudential policy).

consider credit growth volatility as a sole financial stability measure, it is expected that macroprudential policies will stabilize the economy by decreasing volatility more, when employed besides monetary policy.

One important question that has not been fully answered within the literature is whether macroprudential and monetary policy instruments are complements or substitutes. There are some studies obtained via DSGE models and empirical analysis suggests that the two policies are complements.[26] Agénor et al. (2014) claim both types of policy should work in the same direction. Figure (4) highlights the response of credit growth, credit growth volatility, industrial production growth and inflation to a macroprudential policy shock. Figure (4) indicates that macroprudential policy in isolation have similar effects on credit growth and credit growth volatility when compared with the effect of monetary policy within the framework of model 2. However, as noted byAkinci and Olmstead-Rumsey (2018), macroprudential policy is seldom used in isolation. One important observation in Figure (4) is that macroprudential shock does not have a significant effect on the industrial production growth rate. This result is very favourable as this time credit growth and credit growth volatility declines without and significant effect on economic growth.

When we compare our impulse responses with the ones in similar studies, we can see that our results are not very different and mostly the effects of macroprudential policy shocks are very short-lived. For example, Tovar Mora et al. (2012) confirm that macroprudential measures lead to a modest and temporary reduction in private bank credit growth. In their paper, the strongest impact is observed for the case of average reserve requirements and even the effects for reserve requirements are very short-lived for Latin American countries. Chen et al. (2017), in their paper show that the response of industrial production and consumer prices fade out in seven months, i.e. their impulse responses are comparable short-lived for China. The impulse responses in a paper by Kim and Lee (2017) also are either insignificant or very short-lived. Tillmann (2015) find out that the responses of macroprudential tightening on credit growth and housing prices for Korea is only for four months.

Table (4) complements the impulse response analysis with a study of the variance decompositions, which show the relative cumulative contribution of each of the variables in the system. Table (4) reports the fraction of the forecast variance of row variables attributable to innovations in column variables, thereby indicating various degrees of importance of each variable in explaining variation of all other variables. We consider the forecast horizons of 10 periods (months) and note that longer horizons produce almost identical results because all of the responses converge to zero before the 10-month mark. Therefore we only report the 10-month long horizon for variance decompositions. We can clearly observe that without the macroprudential policy tightening variable in the system, policy rate can only explain 2.5 percent of the credit growth and 0.1 percent of the credit growth volatility. When we include the macroprudential policy tightening variable in the panel VAR, policy rate can explain 11 percent of the credit growth and 11.5 percent of the credit growth volatility.

[26] See Angelini et al. (2012), Lambertini et al. (2013) and Alpanda et al. (2014).

Table 4
Variance decompositions.

	ΔIP	ΔPR	ΔLR	ΔCRD	ΔCPI	$CRD-VOL$
Model 1						
ΔIP	0.649	0.057	0.029	0.167	0.087	0.011
ΔPR	0.048	0.557	0.017	0.057	0.303	0.018
ΔLR	0.102	0.224	0.535	0.070	0.052	0.016
ΔCRD	0.059	0.025	0.085	0.579	0.151	0.101
ΔCPI	0.005	0.066	0.003	0.045	0.881	0.001
$CRD-VOL$	0.009	0.001	0.066	0.089	0.014	0.822
	ΔIP	ΔPR	$Pr-Map$	ΔLR	ΔCRD	ΔCPI	$CRD-VOL$
Model 2							
ΔIP	0.610	0.078	0.029	0.049	0.137	0.088	0.010
ΔPR	0.043	0.615	0.031	0.031	0.016	0.248	0.016
$Pr-Map$	0.116	0.144	0.509	0.174	0.019	0.031	0.008
ΔLR	0.141	0.246	0.178	0.363	0.051	0.014	0.007
ΔCRD	0.133	0.110	0.035	0.098	0.423	0.136	0.064
ΔCPI	0.029	0.082	0.047	0.039	0.004	0.799	0.000
$CRD-VOL$	0.111	0.115	0.015	0.097	0.141	0.016	0.505

Note: Percent of variation in the row variable (10 periods ahead) explained by column variable. ΔIP is the monthly logarithmic difference of seasonally adjusted industrial production index. ΔPR is the monthly difference of policy rate. $Pr-MaP$ is the macroprudential tightening probability. ΔLR is the monthly difference of consumer loan rates. ΔCRD is the monthly logarithmic difference of consumer loans. ΔCPI is the monthly logarithmic difference of seasonally adjusted consumer price index. $CRD-VOL$ is the volatility of consumer loans.

Indeed, without macroprudential policy incorporated in the system 82.2 percent of credit volatility is explained by itself and this rate decreases to 50.5 percent with the macroprudential policy variable.

As a robustness check we conduct sensitivity analysis with respect to the order of the variables in the Cholesky decomposition. Accordingly, we do not change the place of industrial production growth, which is the first variable, and credit growth volatility variable, which is the last variable within the Cholesky ordering. Recall that industrial production growth is the proxy for GDP growth, which represents general macroeconomic conditions in our system and as such it is expected to affect all other variables contemporaneously, while it is affected by all others with a lag. As mentioned before, volatility is not immediately observable and can only be inferred after some period, therefore, credit growth volatility is always at the end of the Cholesky ordering. Specifically we consider the following variations of our basic model:

$$(1)\Delta IP \rightarrow \Delta PR \rightarrow \Delta LR \rightarrow Pr-MaP \rightarrow \Delta CRD \rightarrow \Delta CPI \rightarrow CRD-VOL$$

$$(2)\Delta IP \rightarrow \Delta PR \rightarrow \Delta CRD \rightarrow \Delta LR \rightarrow Pr-MaP \rightarrow \Delta CPI \rightarrow CRD-VOL$$

$$(3)\Delta IP \rightarrow \Delta CPI \rightarrow \Delta PR \rightarrow \Delta CRD \rightarrow \Delta LR \rightarrow Pr-MaP \rightarrow CRD-VOL$$

$$(4)\Delta IP \rightarrow \Delta CPI \rightarrow \Delta CRD \rightarrow \Delta PR \rightarrow \Delta LR \rightarrow Pr-MaP \rightarrow CRD-VOL$$

$$(5)\Delta IP \rightarrow \Delta CPI \rightarrow \Delta PR \rightarrow \Delta LR \rightarrow Pr-MaP \rightarrow \Delta CRD \rightarrow CRD-VOL$$

$$(6)\Delta IP \rightarrow Pr-MaP \rightarrow \Delta PR \rightarrow \Delta CRD \rightarrow \Delta LR \rightarrow \Delta CPI \rightarrow CRD-VOL$$

We find that the dynamics of our policy rate and macroprudential tightening probability, as well as variance decompositions, are immune to changing the order of variables. Changing the order of variables does not alter the feedback effects of the overall macroprudential policy and monetary policy on other variables. Hence, our results hold up when alternative orderings are examined.[27]

[27] All detailed results from the robustness exercises are available upon request.

4. Concluding remarks

The recent global financial crisis has made it clear that the macroprudential dimension of financial stability cannot be ignored. Especially after the global crisis many countries have gained valuable experience in the use of macroprudential policies but there are still unclear issues with respect to their policy implementation. One of the issues is the evaluation of the impact of macroprudential policies, especially the iimpact of these policies in cooperation with the monetary policy, on the stability of the financial system and macroeconomy. Currently, the evidence on the impact of macroprudential policies is mixed and additional work is required before one can reach solid conclusions.

This paper assesses the effects of Turkey's macroprudential measures on the consumer loan growth and loan growth volatility since December 2005. Doing so, we present a special emphasis on the interaction between monetary policy and macroprudential policy tools. In this framework, we employ a Panel VAR that includes latent macroprudential tightening probability, monetary policy rate, credit growth, credit growth volatility and some other macroeconomic variables. We obtain latent macroprudential tightening probability by means of instrumental variable probit and credit growth volatility by applying a variety of stochastic volatility models. Our empirical results suggest that Turkey's macroprudential policies have been effective in alleviating consumer credit market vulnerability. In particular, we can observe this effect in a more comprehensive manner when macroprudential policies are used in cooperation with monetary policy. Monetary policy can affect credit growth and credit growth volatility and this effect is more powerful when we combine monetary policy with macroprudential policy. Our analysis confirms that monetary policy benefits from greater use of macroprudential policies, as monetary policy alone is not as effective as when it is used with macroprudential instruments to limit credit growth and stabilize credit volatility. This is, to our knowledge, the first empirical paper that illustrates the impact of macroprudential policy on credit growth volatility.

Future research is required in several areas. First of all, we have only examined the effectiveness of macroprudential policies and monetary policy in few dimensions: its effects on aggregate consumer loan items and their volatilities. However, a more comprehensive analysis should gauge the role of these policies in other

relevant dimensions, such as its impact on the funding structure of the banks or by examining the effects of these macroprudential policies on the riskiness of the banks. To do so, it would be beneficial to conduct this analysis with micro bank level data. Second, this study is conducted only for Turkey, in this respect a more comprehensive analysis will include a cross section of other countries that employ variety of macroprudential policies. With no doubt, it would be interesting to observe the interaction of monetary and macroprudential policies, encountering a wide spectrum of different countries into the study.

Appendices

Priors related to stochastic volatility models

The same hyperparameters are chosen for the parameters that are common across models. For the standard SV, following independent priors are assumed for μ, μ_h, ϕ_h and ω_h^2:

$$\begin{pmatrix} \mu \sim \mathcal{N}(\mu_0, V_\mu), & \mu_h \sim \mathcal{N}\left(\mu_{h0}, V_{\mu h}\right), \\ \phi_h \sim \mathcal{N}(\phi_{h0}, V_{\phi_h})1(|\phi_h| < 1), & \omega_h^2 \sim \mathcal{IG}(\nu_h, S_h), \end{pmatrix} \tag{4}$$

Where $\mathcal{IG}(.,.)$ denotes the inverse-gamma distribution. We set $\mu_0 = 0, \mu_{h0} = 1, V_\mu = V_{\mu h} = 10, \phi_{h0} = 0.97, V_{\phi_h} = 0.1^2, \nu_h = 5$ and $S_h = 0.16$.

For the SV-2, we assume the same priors for μ, μ_h and ω_h^2 as in Eq. (4), but replace the prior ϕ_h with a prior for $\theta_h = (\phi_h, \rho_h)' : \theta_h \sim \mathcal{N}(\theta_{h0}, V_{theta_h})1(\theta_h \in A)$, where $\theta_{h0} = (0.97, 0)', V_{\theta_h} = diag(0.1^2, 1)$ and $A \subset \mathbb{R}^2$ is the set where the roots of the characteristic polynomial defined by θ_h lie outside the unit circle. For the SV-L, correlation parameter ρ is assumed to have the uniform prior $\rho \sim \mathcal{U}(-1, 1)$.

Macroprudential policy actions

Parameter posterior means and standard deviations

Table A2
Parameter posterior means and standard deviations (in parentheses) for the stochastic volatility models (Credit Cards)

	SV	SV-2	SV-J	SV-M	SV-MA	SV-t	SV-L
μ	0.26	0.26	0.27	0.23	0.27	0.26	0.25
	(0.05)	(0.05)	(0.05)	(0.34)	(0.03)	(0.05)	(0.06)
μ_h	0.50	0.50	0.49	0.50	0.36	0.48	0.51
	(0.07)	(0.06)	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)
ϕ_h	0.80	0.90	0.81	0.79	0.80	0.80	0.80
	(0.07)	(0.08)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
ω_h^2	0.02	0.02	0.02	0.02	0.02	0.02	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ρ_h	–	−0.43	–	–	–	–	–
	–	(0.20)	–	–	–	–	–
κ	–	–	0.02	–	–	–	–
	–	–	(0.02)	–	–	–	–
μ_k	–	–	−0.37	–	–	–	–
	–	–	(0.70)	–	–	–	–
σ_k^2	–	–	8.43	–	–	–	–
	–	–	(13.35)	–	–	–	–
λ	–	–	–	0.02	–	–	–
	–	–	–	(0.21)	–	–	–
ψ	–	–	–	–	−0.40	–	–
	–	–	–	–	(0.04)	–	–
ν	–	–	–	–	–	73.54	–
	–	–	–	–	–	(18.51)	–
ρ	–	–	–	–	–	–	−0.25
	–	–	–	–	–	–	(0.39)
$Q(24)$	1257.52	1250.28	1223.70	1253.26	959.47	1256.80	1249.44
	(21.14)	(19.35)	(51.87)	(23.38)	(37.42)	(21.27)	(23.23)
$Q^2(24)$	248.19	239.29	238.68	244.24	169.29	246.88	241.84
	(23.87)	(21.19)	(28.71)	(24.46)	(20.23)	(24.00)	(23.25)

Note: $Q(24)$ and $Q^2(24)$ are respectively the Ljung-Box and McLeod-Li statistics of order 24 computed on the standardized residuals and squared standardized residuals. The 5% and 1% critical values are 36.42 and 42.98 respectively.

Table A1
Macroprudential tools

Date	Macroprudential policy type	Effective on
November 2006	Provisioning	Credit cards/General purpose/Housing/Vehicle
February 2008	Provisioning	Credit cards/General purpose/Housing/Vehicle
March 2008	Adjustment in risk weights	Credit cards
June 2009	Restrictions on FX lending	Credit cards/General purpose/Housing/Vehicle
September 2010	Tax	Credit cards/General purpose/Vehicle
December 2010	Minimum payment rate	Credit cards
January 2011	LTV	Housing
June 2011	Minimum payment rate	Credit cards
June 2011	Provisioning	General purpose
June 2011	Credit growth limit	Credit cards
June 2011	Adjustment in risk rates	General purpose
December 2011	Minimum payment rate	Credit cards
December 2012	Minimum payment rate	Credit cards
June 2013	Minimum payment rate	Credit cards
October 2013	Provisioning	Credit cards/Vehicle
October 2013	Credit growth limit	Credit cards
October 2013	Adjustment in risk weights	Credit cards/Vehicle
December 2013	Minimum payment rate	Credit cards
December 2013	Maturity restriction	General purpose/Vehicle
January 2014	Minimum payment rate	Credit cards
February 2014	LTV	Vehicle
February 2014	Maturity restriction	Credit cards
May 2014	Maturity restriction	Credit cards
January 2015	Minimum payment rate	Credit cards

Table A3
Parameter posterior means and standard deviations (in parentheses) for the stochastic volatility models (General Purpose)

	SV	SV-2	SV-J	SV-M	SV-MA	SV-t	SV-L
μ	0.35	0.36	0.35	0.02	0.35	0.35	0.36
	(0.02)	(0.02)	(0.02)	(0.06)	(0.02)	(0.02)	(0.02)
μ_h	−1.07	−1.25	−1.06	−1.39	−1.06	−1.06	−1.36
	(0.97)	(0.46)	(1.00)	(0.65)	(1.00)	(1.01)	(0.56)
ϕ_h	0.99	0.96	0.99	0.99	0.99	0.99	0.98
	(0.01)	(0.07)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ω_h^2	0.02	0.04	0.02	0.02	0.02	0.02	0.02
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
ρ_h	–	−0.00	–	–	–	–	–
	_	(0.09)	–	–	–	–	–
κ	–	–	0.00	–	–	–	–
	_	–	(0.01)	–	–	–	–
μ_k	–	–	−0.03	–	–	–	–
	_	–	(0.26)	–	–	–	–
σ_k^2	–	–	12.55	–	–	–	–
	_	–	(14.97)	–	–	–	–
λ	–	–	–	1.67	–	–	–
	_	–	–	(0.30)	–	–	–
ψ	–	–	–	–	−0.01	–	–
	_	–	–	–	(0.03)	–	–
ν	–	–	–	–	–	69.33	–
	_	–	–	–	–	(19.95)	–
ρ	–	–	–	–	–	–	0.16
	_	–	–	–	–	–	(0.11)
$Q(24)$	926.58	934.19	920.69	634.56	936.01	928.66	930.94
	(42.16)	(49.54)	(45.76)	(23.91)	(48.81)	(42.35)	(43.39)
$Q^2(24)$	183.28	182.54	183.08	177.50	181.53	181.47	187.99
	(28.46)	(31.34)	(29.62)	(29.42)	(28.35)	(28.59)	(29.38)

Note: $Q(24)$ and $Q^2(24)$ are respectively the Ljung-Box and McLeod-Li statistics of order 24 computed on the standardized residuals and squared standardized residuals. The 5% and 1% critical values are 36.42 and 42.98 respectively.

Table A4
Parameter posterior means and standard deviations (in parentheses) for the stochastic volatility models (Housing)

	SV	SV-2	SV-J	SV-M	SV-MA	SV-t	SV-L
μ	0.33	0.33	0.33	−0.46	0.34	0.33	0.32
	(0.01)	(0.01)	(0.01)	(0.06)	(0.02)	(0.01)	(0.01)
μ_h	−2.31	−1.69	−2.31	−3.47	−2.45	−2.33	−2.72
	(0.87)	(1.10)	(0.90)	(0.27)	(0.95)	(0.90)	(0.37)
ϕ_h	0.98	1.00	0.97	0.97	0.98	0.98	0.95
	(0.01)	(0.07)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
ω_h^2	0.07	0.07	0.08	0.01	0.06	0.08	0.10
	(0.02)	(0.02)	(0.02)	(0.00)	(0.02)	(0.02)	(0.03)
ρ_h	–	−0.01	–	–	–	–	–
	_	(0.07)	–	–	–	–	–
κ	–	–	0.00	–	–	–	–
	_	–	(0.00)	–	–	–	–
μ_k	–	–	0.00	–	–	–	–
	_	–	(0.21)	–	–	–	–
σ_k^2	–	–	26.48	–	–	–	–
	_	–	(99.20)	–	–	–	–
λ	–	–	–	28.42	–	–	–
	_	–	–	(3.44)	–	–	–
ψ	–	–	–	–	0.39	–	–
	_	–	–	–	(0.03)	–	–
ν	–	–	–	–	–	71.35	–
	_	–	–	–	–	(19.40)	–
ρ	–	–	–	–	–	–	0.16
	_	–	–	–	–	–	(0.07)
$Q(24)$	1619.77	1601.54	1605.05	70.17	994.83	1597.37	1596.37
	(146.80)	(142.16)	(144.74)	(9.65)	(88.00)	(153.50)	(143.53)
$Q^2(24)$	35.69	34.18	34.86	18.03	34.17	34.57	35.86
	(10.60)	(10.21)	(10.31)	(5.04)	(6.61)	(9.85)	(11.29)

Note: $Q(24)$ and $Q^2(24)$ are respectively the Ljung-Box and McLeod-Li statistics of order 24 computed on the standardized residuals and squared standardized residuals. The 5% and 1% critical values are 36.42 and 42.98 respectively.

Table A5
Parameter posterior means and standard deviations (in parentheses) for the stochastic volatility models (Vehicle)

	SV	SV-2	SV-J	SV-M	SV-MA	SV-t	SV-L
μ	−0.03	−0.03	−0.03	−1.47	−0.04	−0.03	−0.03
	(0.02)	(0.02)	(0.02)	(0.12)	(0.03)	(0.02)	(0.02)
μ_h	−1.43	−1.36	−1.46	−2.50	−1.57	−1.45	−1.44
	(0.25)	(0.39)	(0.33)	(0.13)	(0.20)	(0.28)	(0.25)
ϕ_h	0.95	1.01	0.96	0.87	0.94	0.95	0.94
	(0.02)	(0.08)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
ω_h^2	0.08	0.09	0.05	0.03	0.06	0.07	0.08
	(0.02)	(0.03)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
ρ_h	–	−0.09	–	–	–	–	–
	_	(0.10)	–	–	–	–	–
κ	–	–	0.02	–	–	–	–
	_	–	(0.01)	–	–	–	–
μ_k	–	–	0.60	–	–	–	–
	_	–	(0.30)	–	–	–	–
σ_k^2	–	–	5.69	–	–	–	–
	_	–	(9.05)	–	–	–	–
λ	–	–	–	17.22	–	–	–
	_	–	–	(2.94)	–	–	–
ψ	–	–	–	–	0.33	–	–
	_	–	–	–	(0.03)	–	–
ν	–	–	–	–	–	60.21	–
	_	–	–	–	–	(22.93)	–
ρ	–	–	–	–	–	–	0.13
	_	–	–	–	–	–	(0.07)
$Q(24)$	946.53	974.78	925.67	212.26	745.17	937.23	957.09
	(90.72)	(113.35)	(99.28)	(35.12)	(53.01)	(89.10)	(90.00)
$Q^2(24)$	112.41	113.07	82.94	38.70	101.35	108.00	117.49
	(23.54)	(25.36)	(21.63)	(16.02)	(23.11)	(24.27)	(24.81)

Note: $Q(24)$ and $Q^2(24)$ are respectively the Ljung-Box and McLeod-Li statistics of order 24 computed on the standardized residuals and squared standardized residuals. The 5% and 1% critical values are 36.42 and 42.98 respectively.

PVAR coefficient estimates and standard errors

Table A6
Model 1

	Coef.	Std. Err.	z	$P>\|z\|$	[95% Conf.	Interval]
ΔIP *equation*						
ΔIP_{t-1}	0.003	0.049	0.050	0.958	−0.094	0.099
ΔPR_{t-1}	−0.014	0.002	−9.260	0.000	−0.017	−0.011
ΔLR_{t-1}	0.004	0.001	4.710	0.000	0.002	0.006
ΔCRD_{t-1}	0.584	0.085	6.900	0.000	0.418	0.750
ΔCPI_{t-1}	1.589	0.215	7.400	0.000	1.168	2.010
$CRD-VOL_{t-1}$	−0.101	0.011	−9.470	0.000	−0.122	−0.080
ΔVIX_{t-1}L1	0.001	0.003	0.180	0.859	−0.006	0.007
ΔVIX_{t-2}	−0.008	0.003	−3.080	0.002	−0.014	−0.003
ΔPR *equation*						
ΔIP_{t-1}	−6.196	1.317	−4.700	0.000	−8.777	−3.615
ΔPR_{t-1}	0.190	0.047	4.080	0.000	0.099	0.282
ΔLR_{t-1}	0.113	0.028	4.060	0.000	0.059	0.168
ΔCRD_{t-1}	8.723	2.631	3.320	0.001	3.567	13.879
ΔCPI_{t-1}	102.404	8.855	11.560	0.000	85.049	119.759
$CRD-VOL_{t-1}$	−2.697	0.328	−8.230	0.000	−3.339	−2.054
ΔVIX_{t-1}	0.714	0.087	8.160	0.000	0.542	0.885
ΔVIX_{t-2}	−0.303	0.078	−3.860	0.000	−0.456	−0.149
ΔLR *equation*						
ΔIP_{t-1}	−26.563	2.701	−9.830	0.000	−31.857	−21.269
ΔPR_{t-1}	0.727	0.081	8.970	0.000	0.568	0.886
ΔLR_{t-1}	−0.213	0.057	−3.740	0.000	−0.324	−0.101
ΔCRD_{t-1}	15.047	5.178	2.910	0.004	4.899	25.196
ΔCPI_{t-1}	31.759	12.068	2.630	0.008	8.106	55.411
$CRD-VOL_{t-1}$	−4.059	0.648	−6.270	0.000	−5.328	−2.790

(*continued on next page*)

Table A6 (*continued*)

	Coef.	Std. Err.	z	P > |z|	[95% Conf.	Interval]
ΔVIX_{t-1}	0.309	0.137	2.250	0.024	0.040	0.577
ΔVIX_{t-2}	−0.082	0.151	−0.550	0.585	−0.378	0.213
ΔCRD *equation*						
ΔIP_{t-1}	0.198	0.045	4.390	0.000	0.109	0.286
ΔPR_{t-1}	0.001	0.001	0.480	0.634	−0.002	0.003
ΔLR_{t-1}	−0.003	0.001	−3.530	0.000	−0.005	−0.001
ΔCRD_{t-1}	−0.215	0.081	−2.650	0.008	−0.374	−0.056
ΔCPI_{t-1}	1.903	0.278	6.860	0.000	1.359	2.448
$CRD-VOL_{t-1}$	0.147	0.011	13.130	0.000	0.125	0.169
ΔVIX_{t-1}	0.011	0.003	3.660	0.000	0.005	0.017
ΔVIX_{t-2}	−0.002	0.003	−0.650	0.515	−0.007	0.004
ΔCPI *equation*						
ΔIP_{t-1}	−0.009	0.009	−1.000	0.316	−0.028	0.009
ΔPR_{t-1}	−0.001	0.000	−1.700	0.089	−0.001	0.000
ΔLR_{t-1}	0.000	0.000	−2.380	0.017	−0.001	0.000
ΔCRD_{t-1}	−0.059	0.018	−3.340	0.001	−0.094	−0.025
ΔCPI_{t-1}	0.315	0.045	6.940	0.000	0.226	0.404
$CRD-VOL_{t-1}$	0.004	0.002	1.940	0.052	0.000	0.008
ΔVIX_{t-1}	0.004	0.001	6.830	0.000	0.003	0.005
ΔVIX_{t-2}	0.000	0.001	−0.050	0.956	−0.001	0.001
$CRD-VOL$ *equation*						
ΔIP_{t-1}	−0.090	0.069	−1.310	0.191	−0.224	0.045
ΔPR_{t-1}	0.000	0.002	0.260	0.793	−0.003	0.004
ΔLR_{t-1}	−0.002	0.001	−1.470	0.140	−0.005	0.001
ΔCRD_{t-1}	0.124	0.118	1.040	0.297	−0.109	0.356
ΔCPI_{t-1}	1.041	0.384	2.710	0.007	0.288	1.793
$CRD-VOL_{t-1}$	0.882	0.018	49.850	0.000	0.847	0.917
ΔVIX_{t-1}	0.006	0.004	1.540	0.123	−0.002	0.014
ΔVIX_{t-1}	0.001	0.004	0.340	0.731	−0.007	0.010

Definitions: ΔIP is the monthly logarithmic difference of seasonally adjusted industrial production index. ΔPR is the monthly difference of policy rate. $Pr-MaP$ is the macroprudential tightening probability. ΔLR is the monthly difference of consumer loan rates. ΔCRD is the monthly logarithmic difference of consumer loans. ΔCPI is the monthly logarithmic difference of seasonally adjusted consumer price index. $CRD-VOL$ is the volatility of consumer loans. ΔVIX is the monthly logarithmic difference of VIX.

Table A7
Model 2.

	Coef.	Std. Err.	z	P > |z|	[95% Conf.	Interval]
ΔIP *equation*						
ΔIP_{t-1}	0.030	0.050	0.600	0.550	−0.068	0.128
ΔPR_{t-1}	−0.014	0.001	−11.350	0.000	−0.017	−0.012
$Pr-Map_{t-1}$	0.007	0.004	1.610	0.106	−0.001	0.015
ΔLR_{t-1}	0.004	0.001	5.560	0.000	0.003	0.006
ΔCRD_{t-1}	0.614	0.075	8.210	0.000	0.467	0.760
ΔCPI_{t-1}	1.676	0.184	9.120	0.000	1.315	2.036
$CRD-VOL_{t-1}$	−0.101	0.009	−10.840	0.000	−0.120	−0.083
ΔVIX_{t-1}	−0.002	0.003	−0.600	0.549	−0.007	0.004
ΔVIX_{t-2}	−0.011	0.003	−4.490	0.000	−0.016	−0.006
ΔPR *equation*						
ΔIP_{t-1}	−7.709	1.167	−6.610	0.000	−9.997	−5.422
ΔLR_{t-1}	0.410	0.045	9.050	0.000	0.322	0.499
$Pr-Map_{t-1}$	−0.583	0.169	−3.440	0.001	−0.915	−0.251
ΔLR_{t-1}	0.079	0.027	2.970	0.003	0.027	0.132
ΔCRD_{t-1}	2.281	2.581	0.880	0.377	−2.778	7.340
ΔCPI_{t-1}	91.767	7.724	11.880	0.000	76.628	106.905
$CRD-VOL_{t-1}$	−1.880	0.318	−5.900	0.000	−2.504	−1.255
ΔVIX_{t-1}	0.788	0.081	9.740	0.000	0.630	0.947
ΔVIX_{t-2}	−0.348	0.071	−4.910	0.000	−0.487	−0.209
$Pr-Map$ *equation*						
ΔIP_{t-1}	1.473	0.533	2.760	0.006	0.428	2.519
ΔPR_{t-1}	0.052	0.016	3.230	0.001	0.020	0.084
$Pr-Map_{t-1}$	−0.420	0.057	−7.400	0.000	−0.531	−0.308
ΔLR_{t-1}	0.084	0.010	8.590	0.000	0.065	0.103
ΔCRD_{t-1}	−2.471	0.888	−2.780	0.005	−4.211	−0.731
ΔCPI_{t-1}	11.436	2.707	4.220	0.000	6.130	16.742
$CRD-VOL_{t-1}$	−0.019	0.111	−0.170	0.864	−0.237	0.198
ΔVIX_{t-1}	0.016	0.031	0.510	0.612	−0.044	0.075
ΔVIX_{t-2}	−0.200	0.030	−6.730	0.000	−0.259	−0.142

Table A7 (*continued*)

	Coef.	Std. Err.	z	P > |z|	[95% Conf.	Interval]
ΔLR_{t-1} *equation*						
ΔIP_{t-1}	−30.977	3.780	−8.200	0.000	−38.385	−23.569
ΔPR_{t-1}	1.816	0.121	14.990	0.000	1.578	2.053
$Pr-Map_{t-1}$	−4.244	0.422	−10.060	0.000	−5.070	−3.417
ΔLR_{t-1}	−0.323	0.074	−4.370	0.000	−0.468	−0.178
ΔCRD_{t-1}	−29.127	6.516	−4.470	0.000	−41.897	−16.356
ΔCPI_{t-1}	−15.524	16.409	−0.950	0.344	−47.685	16.637
$CRD-VOL_{t-1}$	0.882	0.770	1.140	0.252	−0.628	2.392
ΔVIX_{t-1}	0.666	0.185	3.600	0.000	0.303	1.029
ΔVIX_{t-2}	0.424	0.205	2.070	0.038	0.023	0.826
ΔCRD_{t-1} *equation*						
ΔIP_{t-1}	0.174	0.036	4.870	0.000	0.104	0.245
ΔPR_{t-1}	−0.003	0.001	−2.640	0.008	−0.005	−0.001
$Pr-Map_{t-1}$	0.015	0.004	4.030	0.000	0.008	0.023
ΔLR_{t-1}	−0.003	0.001	−4.760	0.000	−0.005	−0.002
ΔCRD_{t-1}	0.000	0.066	−0.010	0.994	−0.130	0.129
ΔCPI_{t-1}	1.840	0.226	8.130	0.000	1.397	2.284
$CRD-VOL$	0.118	0.008	15.140	0.000	0.103	0.134
ΔVIX_{t-1}	0.009	0.003	3.560	0.000	0.004	0.014
ΔVIX_{t-2}	−0.005	0.002	−2.030	0.043	−0.010	0.000
ΔCPI *equation*						
ΔIP_{t-1}	−0.002	0.009	−0.180	0.855	−0.019	0.016
ΔPR_{t-1}	−0.002	0.000	−5.630	0.000	−0.003	−0.001
Pr_Map_{t-1}	0.006	0.001	5.550	0.000	0.004	0.008
ΔLR_{t-1}	0.000	0.000	−2.290	0.022	−0.001	0.000
ΔCRD_{t-1}	−0.003	0.018	−0.190	0.847	−0.038	0.031
ΔCPI_{t-1}	0.355	0.052	6.880	0.000	0.254	0.456
$CRD-VOL_{t-1}$	−0.003	0.002	−1.260	0.209	−0.007	0.002
ΔVIX_{t-1}	0.003	0.001	5.700	0.000	0.002	0.004
ΔVIX_{t-2}	−0.001	0.001	−1.590	0.112	−0.002	0.000
$CRD-VOL$ *equation*						
ΔIP_{t-1}	−0.024	0.058	−0.410	0.683	−0.136	0.089
ΔPR_{t-1}	−0.006	0.002	−3.520	0.000	−0.010	−0.003
$Pr-Map_{t-1}$	0.024	0.006	4.160	0.000	0.013	0.036
ΔLR_{t-1}	−0.002	0.001	−2.050	0.040	−0.005	0.000
ΔCRD_{t-1}	0.339	0.094	3.590	0.000	0.154	0.523
ΔCPI_{t-1}	0.998	0.323	3.100	0.002	0.366	1.631
$CRD-VOL_{t-1}$	0.853	0.013	66.590	0.000	0.827	0.878
ΔVIX_{t-1}	0.006	0.004	1.440	0.150	−0.002	0.014
ΔVIX_{t-2}	0.002	0.004	0.610	0.539	−0.005	0.010

Definitions: ΔIP is the monthly logarithmic difference of seasonally adjusted industrial production index. ΔPR is the monthly difference of policy rate. $Pr-MaP$ is the macroprudential tightening probability. ΔLR is the monthly difference of consumer loan rates. ΔCRD is the monthly logarithmic difference of consumer loans. ΔCPI is the monthly logarithmic difference of seasonally adjusted consumer price index. *CRD-VOL* is the volatility of consumer loans. ΔVIX is the monthly logarithmic difference of VIX.

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