Universität Hamburg
DER FORSCHUNG | DER LEHRE | DER BILDUNG

FAKULTÄT
FÜR WIRTSCHAFTS- UND
SOZIALWISSENSCHAFTEN

Uncovering Heterogeneous Regional Impacts of Chinese Monetary Policy

Andrew Tsang

WiSo-HH Working Paper Series
Working Paper No. 62
November 2021

WiSo-HH Working Paper Series
Working Paper No. 62
November 2021

Uncovering Heterogeneous Regional Impacts of Chinese Monetary Policy

Andrew Tsang, University of Hamburg

ISSN 2196-8128

Font used: „TheSans UHH" / LucasFonts

Kontakt:

WiSo-Forschungslabor
Von-Melle-Park 5
20146 Hamburg
E-Mail: experiments@wiso.uni-hamburg.de
Web: http://www.wiso.uni-hamburg.de/forschung/forschungslabor/home/

Uncovering Heterogeneous Regional Impacts of Chinese Monetary Policy

Andrew Tsang

Hamburg University
Department of Economics
GERMANY
andrewhctsang@gmail.com

November 2021

Abstract

This paper applies causal machine learning methods to analyze the heterogeneous regional impacts of monetary policy in China. The method uncovers the heterogeneous regional impacts of different monetary policy stances on the provincial figures for real GDP growth, CPI inflation and loan growth compared to the national averages. The varying effects of expansionary and contractionary monetary policy phases on Chinese provinces are highlighted and explained. Subsequently, applying interpretable machine learning, the empirical results show that the credit channel is the main channel affecting the regional impacts of monetary policy. An imminent conclusion of the uneven provincial responses to the "one size fits all" monetary policy is that different policymakers should coordinate their efforts to search for the optimal fiscal and monetary policy mix.

Keywords: China, monetary policy, regional heterogeneity, machine learning, shadow banking

JEL-Classification: E52, C54, R11, E61

1 Introduction

In the past decade, many central banks have used monetary policy to counteract the impacts of the global financial crisis (GFC). The unconventional quantitative easing has raised interest in examining monetary policy impacts, particularly in studying whether a single monetary policy has heterogeneous impacts on regional economies (see Dominguez-Torres and Hierro, 2019 for a review). Actually, this is related to the debate on the "one-size-fits-all" monetary policy, in which a single monetary policy can fit the economic conditions for all regions in large countries (or countries in monetary unions). The latest literature (e.g., Albuquerque, 2019; Wynne and Koech, 2012) suggested that a single monetary policy does not fit all as asymmetric effects on the economic performance across regions are found in the US and across Euroland countries. The heterogeneous territorial effects of monetary policy have been studied since the 1970s. The heterogeneous regional impacts of a single monetary policy are particularly useful for analyzing monetary policy in large countries or monetary unions. For example, Carlino and DeFina (1998, 1999), Furceri et al. (2019), and Pizzuto (2020) studied this issue for the US, and Hauptmeier et al. (2020) for the Euroland countries.

In recent decades, China has gradually changed its monetary policy framework from a repressive financial system to a more market-based system (Funke and Tsang, 2021). The existing literature has shown that China's monetary policy has been tracking the Chinese economy well (see Funke and Tsang, 2021; Kamber and Mohanty, 2018; Sun, 2018). In addition, Funke and Tsang (2020) have shown that China's swift and decisive monetary policy easing since the COVID-19 outbreak has supported the quick rebound of the economy. However, the existing literature mainly focused on the national-level evidence. Given the highly divergent features among different regions in China, heterogeneous regional impacts of the national monetary policy can be expected. Some previous studies, e.g., Cortes and Kong (2007) and Guo and Masron (2014, 2017) have studied the heterogeneous regional impacts of monetary policy for China. However, previous studies have only covered the sample period until 2011, before the recent reforms.

Against this background, this paper will examine the heterogeneous regional impacts of the current Chinese monetary policy. Instead of using conventional monetary policy variables (mainly interest rates), this paper uses the newly developed dynamic factor model (DFM)-based monetary policy indicator (constructed in Funke and Tsang, 2021) and provincial-level data.[1] Specifically, this paper will answer the following: i) Does the current national monetary policy have heterogeneous regional impacts in China? ii) Which regional factors determine the possible heterogeneous impacts of the monetary policy?

Dominguez-Torres and Hierro (2019) summarized that the heterogeneous regional impacts of monetary policy could be varied through three major channels: the interest-rate channel affecting the interest-sensitive industry, the exchange-rate channel influencing the exports through the changes in the exchange rate, and the credit channel affecting the demand for and supply of credits. Therefore, factors related to these three channels will be included. Furthermore, the heterogeneous monetary policy impacts could come from different regional economic structures, which affect the effectiveness of monetary policy transmission.[2] In addition, China-specific factors may also affect the heterogeneous regional policy impacts. For example, the size of the province's shadow banking and the location of the province could be considered.

Starting from the studies of Carlino and DeFina (1998, 1999), the existing literature on the heterogeneous regional effects of monetary policy has mainly used VAR-based models (including local projection models) to evaluate the average impact of monetary policy. Then the average contributions of regional factors over the sample have been assessed. The problem is that this methodology can only assess the average impact of monetary policy by assuming a constant contribution of regional characteristics over the sample, but it cannot evaluate the time-varying impacts and time-specific contribution of regional characteristics on the individual region. In contrast, this paper applies machine learning methodologies to evaluate the effectiveness of Chinese monetary policy at the provincial level. In analyzing the economic causal effects, particularly in obtaining the counterfactual analysis, causal machine learning—like causal forests (Athey et al., 2019)—can provide a "more precise, less biased, and more reliable" estimator for causal inference (Tiffin, 2019). One distinct feature of causal machine learning methods is that they can obtain the "real" counterfactual analysis (Athey and Imbens, 2017). Also, the methods can estimate the time-varying heterogeneous impacts for every observation. Therefore, this paper will estimate both the average and individual heterogeneous impacts of China's monetary policy stances (both easing and tightening) on provincial economies. Specifically, the impacts on gaps in provincial output growth, CPI inflation, and loan

[1] Cortes and Kong (2007), Guo and Masron (2014, 2017) used the official benchmark lending rate or monetary aggregates (M1 or M2) to estimate the regional impacts of Chinese monetary policy.

[2] In the recent decade, the Chinese authorities claimed that the economy was entering a "new normal" with a lower growth rate, and changes in economic structure were expected. Hence, different speeds of changes in economic structure may affect the effectiveness of monetary policy in different regions.

growth from their national average will be analyzed. As there has been no literature showing the application of machine learning methods to the heterogeneous regional impacts of monetary policy, this paper will fill the gap in the literature. Furthermore, this paper will also use the latest developed interpretable machine learning methods to evaluate the possible underlying determinants of heterogeneous monetary policy impacts across provinces.

This paper contributes to the literature in two ways. First, this paper extends the applications to the growing "causal machine learning" literature on policy analysis. This is the first paper applying causal machine learning to the regional impacts of the monetary policy. Moreover, differently from the existing literature that only focused on the regional impacts on economic growth, this paper also assesses the regional impacts on inflation and loan growth. Second, this paper provides new regional-level evidence to assess the effectiveness of China's latest monetary policy in promoting economic growth and maintaining price stability across different provinces. This could shed light on the monetary policy design with a concern to mitigate regional differences.

The remainder of the paper is organized as follows. Section 2 reviews the institutional background and the latest development of China's monetary policy. Section 3 discusses the methodology and data, and Section 4 reports the estimation results. Section 5 concludes the paper.

2 China's Monetary Policy

This section provides the relevant institutional background of current China's monetary policy and major concerns related to the monetary policy formulation. These help to understand the effectiveness of China's monetary policy.

In the recent decade, China has introduced a series of reforms to its monetary policy, from a repressive system, with preset interest rates and lending quotas, to a more market-based system. China's central bank, the People's Bank of China (PBoC), aims to promote economic growth by maintaining price stability, and it has developed a new monetary policy toolkit, including a set of price-based instruments and quantity-based instruments. For the price-based instruments, PBoC set a new policy target of the market-based pledged 7-day repo rate interbank market with a corridor system of interest rates.[3] In addition, China aims to develop a policy interest rate that influences the interbank interest rate, similar to those used in advanced economies and which ultimately affects loan rates through the market mechanism. Meanwhile, PBoC introduced a new standard for all loans using the market-determined one-year loan prime rate (LPR) for lending to prime customers.

For the quantity-based tools, PBoC's policy toolkit includes the reserve requirement ratio (RRR) and other liquidity provision facilities. The RRR is actively used by the PBoC for money supply management, particularly in neutralizing the fluctuations of the domestic money supply caused by changes in foreign reserves. In addition, PBoC can give a clear and strong policy signal to the market through changes in the RRR. Meanwhile, the PBoC uses liquidity provision facilities to steer the target interest rate within the corridor system and fulfill the banking sector's liquidity needs (Funke and Tsang, 2021). Specifically, the liquidity provision facilities include the reverse repo in the open-market operations, the standing lending facility (SLF, a lending facility for funding within a month), the medium-term lending facility (MLF, providing funding from three months to a year), the pledged supplementary lending (PSL, aiming at the nation's three policy banks: China Development Bank, Agricultural Development Bank of China and the Export-Import Bank of China), as well as relending and rediscounting.[4] In steering the corridor system, the PBoC injects or withdraws different sizes of liquidity provision facilities and adjusts the lending rates of these liquidity provision facilities. As a result, the PBoC changes the money supply and interest rates on a short-term basis through these operations.

The market-based reforms have brought Chinese monetary policy closer to the norms in developed economies. However, the multiple-instrument monetary policy framework hinders the assessment of the prevailing policy stance. Against the background of this multitude of price-based and quantity-based monetary policy instruments, Funke and Tsang (2020, 2021) developed a new dynamic factor model (DFM)-based monetary policy indicator. Unlike narrative indicators based on the analysis of official statements in other literature, the DFM-based indicator is a data-driven method to measure the overall monetary policy stance. In contrast to using a single interest rate to measure monetary policy stance, the DFM-based indicator is a comprehensive indicator to consider for the usage of various policy tools. It concludes

[3] The rates of the SLF constitute the upper bound of the corridor, and the lower bound is the interest rate of banks' excessive deposit reserves paid by the PBoC.

[4] In addition, the PBoC also uses some temporary facilities, including contingent reserve arrangements (CRA), short-term liquidity operations (SLO), the targeted medium-term lending facility (TMLF), and the temporary lending facility (TLF).

China's monetary policy stance by extracting the common underlying factor of the movement of different policy tools under the hybrid monetary policy framework.

3 Methodology and Variables

This section discusses the machine learning methods used in this paper to estimate the heterogeneous monetary policy impacts across provinces and to assess their possible determinants. Then the section will discuss the construction of the policy variables. Finally, the variables and data used in the estimation will be discussed.

3.1 Machine Learning

Machine learning involves the methodologies developing algorithms with an objective to identify the best predicted outcomes or data patterns based on the limited information from a specific data set (Tiffin, 2019). In addition, machine learning methodologies have been concerned more with prediction than a model's accuracy and interpretability. A "good" machine-learning model, then, is determined by looking at its likely out-of-sample success.

Machine learning is different from conventional econometrics. Conventional econometrics targets estimating the parameters of the model that best fit the selected sample, by specifying the function of a joint distribution of the data. A "good" econometric model is mostly assessed according to statistical significance and in-sample goodness of fit. Therefore, the quality of the estimators is the main concern of conventional econometrics, and statistical inference is also important. In addition, traditional econometrics has generally focused on explanation, with particular attention to issues of causality and a premium placed on parsimonious models that are easy to interpret. In contrast, as machine learning aims at obtaining the best prediction or classification performance relating to the data, machine learning methods only rely on data-driven model selection, without regard for a priori analytical solutions, implications for inference, and asymptotic properties (see Athey and Imbens, 2019; Chakraborty and Joseph, 2017).

There are two main types of machine learning, namely supervised machine learning and unsupervised machine learning. Supervised machine learning is the method with an outcome variable, which is primarily used for prediction or classification problems. This method uses information from some control variables to predict the outcome variable. Unsupervised machine learning does not have an outcome variable, and it focuses on searching clusters based on patterns in data. In order to search for the best prediction, classification, or clusters, machine learning obtains these by repeatedly splitting the data set into a training sample, a validation sample, and a test sample. Using the prediction problem as an example, a training sample is used for estimation, and the estimation results of the training model are validated and tested by a validation sample. The parameter is selected or tuned according to the prediction performance, e.g., minimizing the squared residuals' sum in the validation samples. Then the estimation results are applied to predict outcomes in the test sample for evaluating the final model. In addition, the sample is split by trying different criteria based on the variables' information in the data set. The final prediction results are estimated and tuned by repeatedly splitting the data set. The procedure is purely data-driven, and the limited information can be fully utilized, as all observations can be used in both training and test samples.

Machine learning could be more useful for some economic problems than traditional econometrics. Compared with econometrics, machine learning methods, e.g., support vector machines and neural networks, are better for detecting severe nonlinearities and high-order interactions (Athey and Imbens, 2019). For example, it is difficult for econometric models to include the interactions of all determinants in predicting a financial crisis. This is because a crisis is also affected by the nonlinearities and interaction of a range of variables. However, machine learning can automatically find the impacts of these nonlinearities and interactions by searching the sample splitting criteria (see Mullainathan and Spiess, 2017).

Another example is measuring the impacts of policy, which is equivalent to estimating the causal effect. Measuring the sizes of policy impacts requires counterfactual analysis, i.e., estimates for the situation without the presence of the policy. However, such observation is not available. Therefore, it is impossible to estimate the causal effect directly, but machine learning can. Measuring the monetary policy impacts is the main issue of this paper, and causal machine learning is particularly useful. The method will be further discussed in the next part.

3.2 Causal Machine Learning and Interpretable Machine Learning

In order to solve the problem of lacking observational data for counterfactual analysis, traditional econometrics has applied different identification strategies or empirical strategies for identifying the causal effect. For instance, regression discontinuity, synthetic control methods, differences-in-differences methods, methods designed for network settings, and methods that combine experimental and observational data are those used by the econometrician. In using these methods, the causal effect can be identified by measuring the average outcome of the policy or treatment, provided that the data set is sufficiently large (Athey and Imbens, 2017). However, the size of macroeconomic data set is always limited.

Athey and Imbens (2017) showed that machine learning methods could improve the credibility of policy evaluation with the combination of predictive methods (supervised machine learning) and causal questions. Specifically, causal machine learning can estimate the average treatment effects (ATEs) for the whole sample or subsamples (subgroups), as well as the heterogeneous treatment effects (HTEs) for individual observations. Furthermore, machine learning has predictive strengths and flexibility, which can improve some estimates, like those with the interaction of a range of variables. In addition, causal machine learning is used more systematically to approach supplementary analyses (such as interpretable machine learning techniques), in which the results can be interpreted to convince the reader and increase the credibility of the primary analyses.

According to the machine learning literature, the heterogeneous treatment effects could be estimated by a causal forest (a random forest (RF)-based methodology, see Athey et al., 2019; Athey and Wager, 2019) or metalearners (built on base algorithms, such as RF, Bayesian additive regression trees (BARTs) or neural networks, see Künzel et al., 2019). Künzel et al. (2019) suggested that causal forests and the meta-learners used with RFs perform similarly, while the metalearners with other base learners could outperform causal forests in some cases (but those cases do not fit this paper). Therefore, this paper will focus on the RF-based methodology, and the causal forest will be used.

Applying the causal forest, the impacts of monetary policy can be estimated through a counterfactual assessment. Specifically, the causal forest estimates the impacts of a policy (a binary treatment, denoted as W) on a specific outcome variable (Y) with controlling for a set of confounding variables (X). In addition, both the policy variable (W, or treatment variable) and the outcome variable (Y) are conditional on the confounding variables (X). The treatment effects (policy impacts) are defined as the differences between the estimated values of Y with and without implementing the policy (i.e., the treatment, *W*), conditional on confounding variables (*X*). One advantage of the causal forest over traditional econometrics is that the causal forest can estimate the treatment effects for each individual observation (also denoted as individual treatment effects, ITEs). Hence, the conditional average treatment effects (CATEs), conditional on confounding variables, can be estimated for the average treatment effects of the whole sample. In addition, CATEs for the selected subsample is suitable for representing the impacts of monetary policy on provincial economic performance.

Essentially, the causal forest is a random forest made up of honest causal trees. "Honest" means that the same outcome data cannot be used in splitting the tree and estimating the average impact simultaneously. Practically, the causal forest uses algorithms to repeatedly divide the data into two groups. One is for determining how to split the tree, and another one is used to estimate the treatment effect in each leaf ("leaf" is a subgroup in the "tree"). Furthermore, with repeated experiments on splitting the data, the similarity among observations in the same leaf can be determined. Since the policy impacts on the outcome (treatment effects) cannot be observed, the causal forest estimates the average difference in outcomes between treated and nontreated observations within each leaf of the tree. Then the causal forest can estimate the treatment effects by searching a splitting rule that finds the splits with the largest difference in treatment effects. Finally, the average effect for different subgroups helps predict the individual effect for future observations with the same set of confounding variables. The causal forest algorithm typically builds thousands of individual trees and uses a new bootstrap sample for each tree, and the algorithm will exploit all the data for both splitting and estimation. This increases the accuracy of the estimates of treatment effects.

Thus, a large number of individual trees are also required for the valid confidence intervals and causal inference (Athey et al., 2019). The causal inference is challenging because the treatment effects based on the counterfactual predictions cannot be validated. Different from the prediction exercise that a predicted outcome can be validated as the outcome can be known in future, the treatment effects are estimated potential outcomes that are unknown. This problem can be mitigated by increasing the randomized experiments (number of trees) for analyzing the same set of data. Increasing the number of randomized experiments improves the accuracy of the estimated treatment effects on average, for which idiosyncratic differences can be cancelled out.

After obtaining treatment effects, interpretable machine learning techniques can be used to analyze the determinants of the treatment effects. Interpretable machine learning

(IML, or explainable AI in some literature) refers to methods and models that decompose and interpret machine learning results (Molnar et al., 2020). This paper uses interpretable machine learning techniques to analyze the contributions of determinants (confounding variables) of the heterogeneous impacts of the single monetary policy on the differences in regional economic variables. Specifically, two methods will be used in this paper.

First, this paper uses the SHapley Additive exPlanations (SHAP) to evaluate the importance of different confounding variables on the heterogeneous policy effects. Specifically, the importance (contribution) of a confounding variable for an observation is defined as the effect on the difference between the predicted treatment effect and the average of all predicted treatment effects, including that confounding variable.[5] The SHAP-based importance of a single confounding variable is estimated using Shapley value analysis across all possible combinations of confounding variables.[6] The importance estimated by SHAP is additive, in which the sum of magnitudes of all confounding variable contributions is equal to the difference between the predicted treatment effect and the average of all predicted treatment effects. The SHAP waterfall chart shows the contribution of each confounding variable on monetary policy impacts for an individual observation. In summarizing the importance of confounding variables for the whole sample, the SHAP variable importance plot, which shows the sum of absolute Shapley values per confounding variable across the sample, can be used.

Second, the partial dependence plot (PDP) is also used in this paper. PDP shows the marginal effects (partial function) of one or two confounding variables on the model output (the predicted treatment effects), for which the partial function can be linear, nonlinear or more complex. Unlike SHAP that finds the influence of confounding factors on the accuracy of the model output, PDP analyzes how much the confounding variables affect the predicted treatment effects at specific ranges of the confounding variables. Thus, the marginal effects of a specific confounding variable represent the causal interpretation for that specific confounding variable on the predicted treatment effects, considering all possibilities (Friedman, 2001). In estimating marginal effects shown in PDP, confounding variables are assumed to be uncorrelated with each other. The marginal effect of a specific confounding variable is estimated by

[5] It is different from permutation importance, which is based on the decrease in the effect on the model performance by removing the specific confounding variable.

[6] Shapley value analysis is a method borrowed from coalitional game theory (Shapley, 1953), which is a method for measuring the contributions of single players in a game to the total payout. The Shapley value is the average marginal contribution of a single player across all possible coalitions. In the context of this paper, the average marginal contribution of a single confounding variable across all possible combinations of confounding variables will be estimated. The details of the calculation of Shapley value and SHAP can be found in Lundberg and Lee (2017) and Molnar (2019), Chapter 5.9 and 5.10.

marginalizing the predicted treatment effects over the marginal distribution of other confounding variables. By marginalizing over the other confounding variables, we can get a function that depends only on the specific confounding variables we are interested in, while its interactions with other confounding variables are included. The partial function (marginal effect) for one or two confounding variables on the predicted treatment effects is estimated by calculating averages in the training data using the Monte Carlo method.[7] The PDP for a single variable displays the predicted policy impacts for different values of a specific confounding variable for the causal forest.[8]

3.3 Monetary Policy Stance

Since monetary policy impacts could be different in the economic upturns and downturns, the impacts in different phases should be examined separately. Therefore, two policy variables must be constructed for two policy stances: monetary easing and monetary tightening.

In this paper, the forward-looking Taylor rule with interest rate smoothing suggested by Clarida et al. (1998, 2000) is used. In contrast to the previous literature (e.g., Zheng et al., 2012), the interest rate is replaced by Funke and Tsang (2020, 2021)'s DFM-based monetary stance indicator. Since monetary policy impacts should be evaluated by separating two policy stances, the regime-switching method can be applied to separate the policy stances in different regimes. In particular, this paper applies the Markov switching model, which Hamilton (1989) suggested and is commonly used in the monetary policy literature.[9] The Markov switching Taylor-rule model is given:

$$M_t = (1 - \rho_{M,S_t})\{c_{S_t} + \beta_{\pi,S_t}\pi^e_{t+1} + \beta_{gap,S_t}gap^e_{t+1}\} + \rho_{M,S_t}M_{t-1} + \varepsilon_t, \tag{1}$$

where M_t is the monetary stance, π^e_{t+1} is the inflation expectation for the next period and β_{π,S_t} is the corresponding coefficient, gap^e_{t+1} is the GDP-based output gap forecast for the next period and β_{gap,S_t} is the corresponding coefficient, ρ_{M,S_t} is the monetary policy smoothing parameter, proxied by the first order autoregressive (AR(1)) coefficient of monetary policy stance, c_{S_t} is the constant term, and the error term (ε_t) is i.i.d. with regime-switching variance,

[7] The details of the calculation of partial function can be found in Molnar (2019), Chapter 5.1.
[8] For the two confounding variables case, the interactive PDP is used to show the predicted policy impacts for combinations of different values of two specific confounding variables.
[9] More details of the Markov switching model can be found in Hamilton (1989). The same methodology has been applied to China in Zheng et al. (2012).

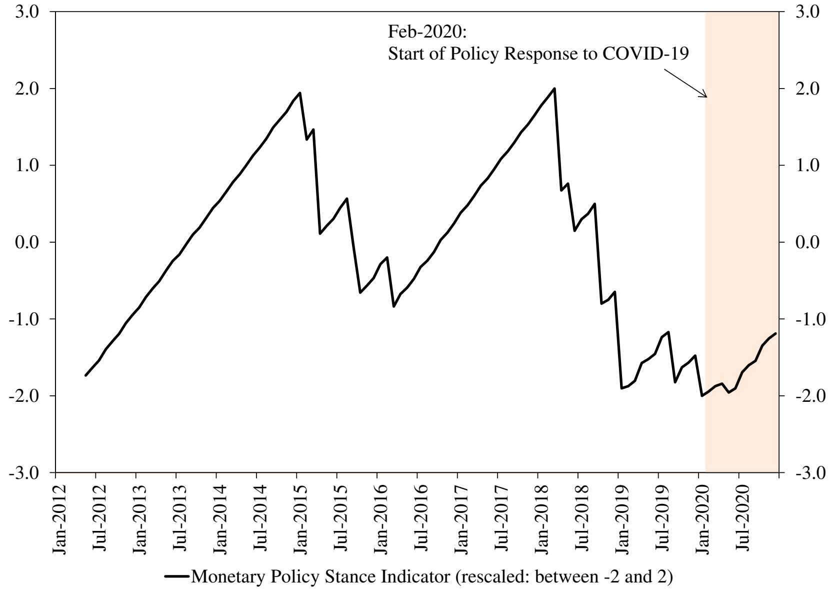
$\varepsilon_t \sim N\left(0, \sigma_{S_t}^2\right)$. All coefficients are regime-dependent and the following transition probabilities govern the unobserved state variable (S_t), for which $S_t = \{1, 2\}$:

$$Pr[S_t = 1 | S_{t-1} = 1] = q, \quad (2)$$

$$Pr[S_t = 2 | S_{t-1} = 2] = p. \quad (3)$$

As discussed above, China's monetary policy is a hybrid approach, and the monetary policy stance presents a bundle of policy tools rather than a single policy rate. Therefore, the DFM-based monetary policy indicator suggested by Funke and Tsang (2021) is used to proxy China's monetary policy stance in this paper. Specifically, the approach estimates a single underlying, unobservable monetary policy stance that captures the comovements in different monetary policy instruments that have a common element. This paper updates the monthly DFM-based monetary policy stance indicator to the end of 2020 (Figure 1).[10] Then, the indicator is converted into quarterly frequencies by taking the average of the indicator within the specific quarter in estimating the forward-looking Taylor rule.

Figure 1. The Development of China's Monetary Policy Stance Indicator



Notes: The monetary policy stance indicator is estimated using the dynamic factor model (DFM) in Funke and Tsang (2020, 2021) and is updated to the end of 2020. Rising values for the indicator represent monetary tightening, while a falling value implies easing.

[10] The updated indicator shows that since the outbreak of the Corona crisis, China had maintained an accommodative monetary stance, although some tightening signs occurred in the second half of 2020 when the Chinese economy recovered and picked up gradually.

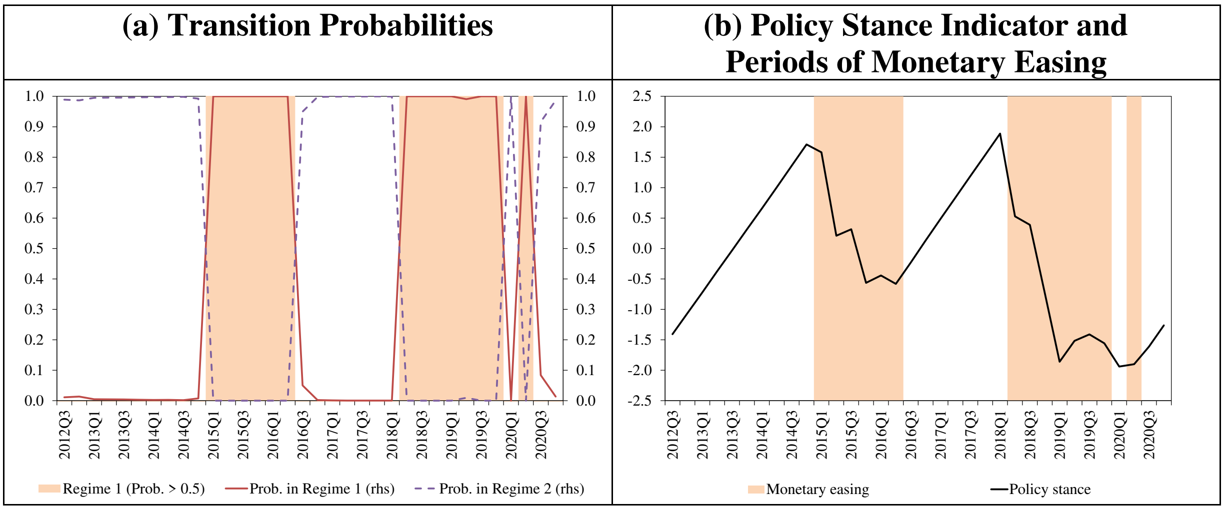
Assuming the central bank adjusts its monetary policy stance cautiously by smoothing the policy stance, the monetary policy smoothing parameter is included in the model, proxied by the AR(1) coefficient of the monetary stance. The output gap (gap_t) is proxied by the difference between the logarithm of real GDP (seasonally adjusted) and its Hodrick-Prescott (HP) trend. The expectations of the output gap and CPI inflation are proxied by the one-step-ahead autoregressive (AR) forecasts, in which the corresponding AR models are estimated up to AR(4). The number of lags is selected by using AIC (Akaike information criterion) and SIC (Schwarz information criterion, aka Bayesian information criterion BIC), and the AR(1) model is chosen for output gap, while AR(4) is chosen for CPI inflation.

Table 1. Estimates of the Markov Switching Taylor-Rule Model

Parameters	Regime 1 (Easing)			Regime 2 (Tightening)		
	Estimate	**SE**	**p-value**	**Estimate**	**SE**	**p-value**
Constant (c_{S_t})	-0.619	(0.304)	[0.042]	0.328	(0.019)	[0.000]
Monetary policy smoothing (ρ_{M,S_t})	0.656	(0.107)	[0.000]	0.997	(0.010)	[0.000]
Inflation expectation (β_{π,S_t})	-0.193	(0.620)	[0.755]	0.187	(0.040)	[0.000]
Expected output gap (β_{gap,S_t})	-45.654	(48.668)	[0.348]	8.725	(0.577)	[0.000]
Log of Sigma ($ln(\sigma_{S_t})$)	-0.800	(0.167)	[0.000]	-3.350	(0.133)	[0.000]
Transition probability matrix						
$\Pr(S_t = 1 \mid S_{t-1})$	0.765			0.145		
$\Pr(S_t = 2 \mid S_{t-1})$	0.235			0.855		
Log-likelihood	45.148					
AIC	-1.950					
SIC	-1.411					

Notes: The table shows the estimated results for the Markov switching Taylor-rule model (equations 1–3). Standard errors (SE) are in parentheses, and p-values are in brackets.

Figure 2. Monetary Policy Stance with Regime Switching (Quarterly)



Notes: The periods of monetary easing (Regime 1) are determined by the Markov switching Taylor-rule model.

Table 1 presents the estimates of equation (1). Both the inflation expectation and expected output gap are insignificant during monetary easing (Regime 1) but significant during monetary tightening (Regime 2). The estimation results suggest that China's monetary policy is asymmetric, as the policy follows Taylor rule during monetary tightening only. The results in Table 1 indicate that Chinese policymakers are more alert to a high inflation rate than a low one, which is consistent with the anti-inflationary nature of China's monetary policy (Girardin et al., 2017). For the expected output gap, similar to Zheng et al. (2012), it is significant in the regime of monetary tightening but insignificant in monetary easing. This confirms findings of Chen et al. (2016) that there are asymmetric responses in China's monetary policy to the economic growth. Panel (a) in Figure 2 shows the estimates of transition probability and indicates the periods in Regime 1 with the corresponding (smoothed) transition probability above 0.5. Panel (b) in Figure 2 indicates that Regime 1 could be specified as the monetary easing period, as it is consistent with the periods with easing policy stances. Hence, the policy variables for monetary easing and monetary tightening can be constructed corresponding to Regime 1 and Regime 2, respectively.

3.4 Outcome Variables and Confounding Variables

Outcome variables

In order to assess the regional impacts of Chinese monetary policy, the outcome variables are defined as gaps in provincial economic variables from the corresponding national averages. Specifically, this paper selects three economic variables: the gaps in provincial real GDP growth, CPI inflation, and loan growth from their national averages, of which economic growth and inflation are PBoC's monetary policy targets. The loan growth is the direct result of the monetary policy.

The outcome variables (provincial real GDP growth, CPI inflation, and loan growth) are constructed by calculating gaps in year-on-year growth of provincial variables from the corresponding national averages of the year-on-year growth in the four quarters ahead of the implementation of the monetary policy stance. The growth rate (or inflation rate) is used to eliminate the issue of nonstationarity. Since the Chinese government has only released the year-on-year growth of macroeconomic variables at the provincial level while the levels and their quarterly seasonally adjusted series are not available, the four-quarter-ahead of the year-on-year growth is used in constructing outcome variables. The national averages are the population-weighted average of the provincial values. Using the weighted average instead of the national value, because the provincial data include the information, could project Chinese aggregate economic growth and reveal fluctuations that have been smoothed in the official growth series for more recent years (see Kerola and Mojon, 2021).[11] Meanwhile, since monetary policy takes time to affect the real economy, this paper defined each outcome variable as the gaps in the cumulative growth rate in the four quarters after implementing monetary policy stance, equivalent to the four-quarter-ahead of the gaps in the year-on-year growth.

Confounding variables

For the underlying factors (confounding variables) determining the heterogeneous regional impacts of the national monetary policy, a set of provincial-level economic variables is included.

1) *The interest rate channel*: the impacts of monetary policy can be affected by the interest sensitivity of production, which can be proxied by the provincial industry mix (Carlino and DeFina, 1998, 1999; Dominguez-Torres and Hierro, 2019). Specifically, the share of tertiary industry ("Tertiary_industry") is included in the list of confounding variables. In addition, the share of tertiary industry also reflects the changes in economic structure, as shifting the production from the manufacturing to service industry was one major reform related to the changes in economic structure in the recent decade.[12]

2) *The exchange rate channel*: Given that different provinces have different importance concerning trade, and it is expected that the monetary policy will have different impacts on the regional economy. Georgopoulos (2009) used the share of exports (value of exports divided by GDP, "Share_Exports") as a proxy for this effect.

3) *The credit channel*: Different levels of credit-market imperfections and asymmetric information in the funding market affect the size of the spread between internal and external funding costs. Dominguez-Torres and Hierro (2019) summarized that this spread affects monetary policy transmission differently through credit demand (broad credit channel) and credit supply (narrow credit channel).

[11] The discrepancy between the aggregation of provincial level economic data and national series in China has raised concerns among researchers. Koch-Weser (2013) has pointed out that the data discrepancy is "a complex problem", as the difference varies across provinces and over time. The problem of overstating economic performance has been improved since the 2000s. Meanwhile, He (2011) argued that the provincial level economic data are reliable for growth regressions.

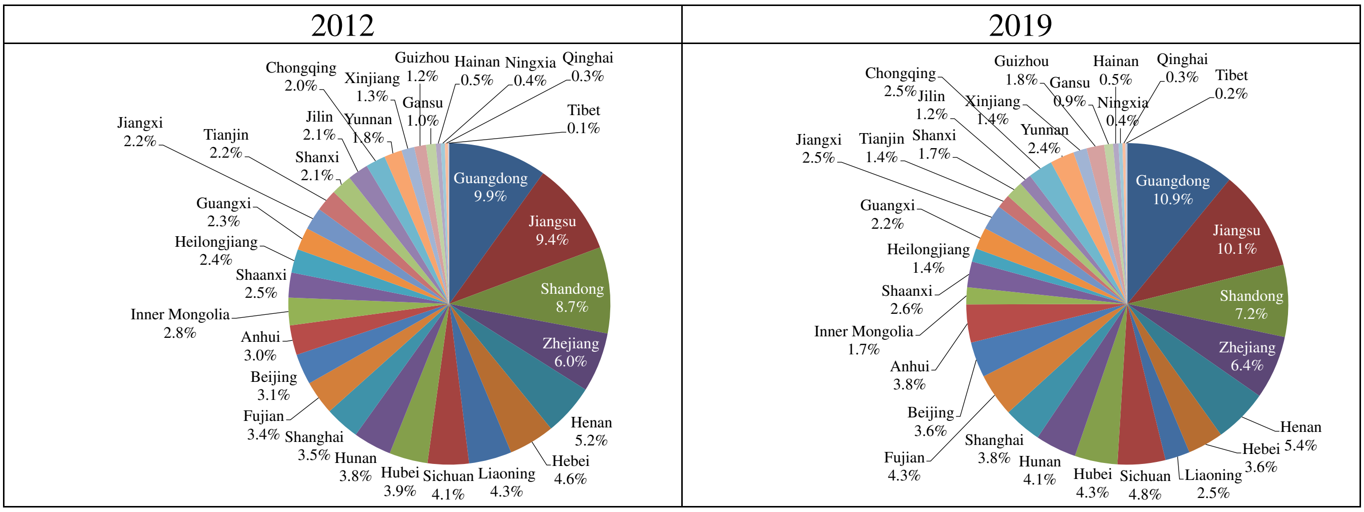
[12] This is also consistent with the shifting from an export-oriented strategy (mainly the output of secondary industry) to promoting domestic consumption (retail sales and services are mainly included in tertiary industry).

- For the credit demand (broad credit channel), the share of the small firm ("Share_small_firm") and the share of state-owned enterprises (SOEs; the variable is denoted as "Share_SOE") are used as proxies for the impacts under this channel (Guo and Masron, 2017).
- The impacts of monetary policy on credit supply (narrow credit channel) could be examined by the share of business loans ("Share_Business_loans"; see Cortes and Kong, 2007) and the share of the small bank ("Share_small_bank").
- In addition, the structure of banks' loan deposits and supply can affect the effectiveness of monetary policy (Girotti, 2018; Horst and Neyer, 2019). Thus, the loan-to-deposit ratio (LTD, and the variable is denoted as "Loan_to_Deposit") is used to proxy for the impacts of funding availability.
- The share of shadow banking ("Share_Shadow_banking") is included, as shadow banking was an important funding source over the last decade (see Chen et al., 2018; Funke et al., 2015, 2019).

4) *Regional dummy*: The locations of provinces can affect the impacts of monetary policies. In particular, provinces in the coastal region grew faster in previous decades (Cortes and Kong, 2007; Guo and Masron, 2014, 2017). Therefore, this paper includes a regional dummy for the provinces in the coastal region ("Coastal", which is the same as the Eastern region defined by the National Bureau of Statistics [NBS]). The list of provinces included in the sample, indicating the provinces in the coastal region, can be found in Appendix 1.

The relative economic position of provinces in China can be illustrated by using the shares of provincial nominal GDP. Figure 3 shows the annual provincial nominal GDP shares of national GDP in 2012 (the first year of the sample) and 2019 (the last year of the sample). The provinces in the coastal region (e.g., Guangdong, Jiangsu, Shandong, and Zhejiang) had the largest shares of national GDP. Most of the provinces had a similar ranking throughout the sample. However, the share and ranking of some provinces changed significantly due to large gaps in growth with other provinces. For example, the share of Liaoning's GDP dropped from 4.3% in 2012 to 2.5% in 2019 due to a lower-than-average growth rate in the past decade.

Figure 3. GDP Shares of Chinese Provinces in Percent, 2012 and 2019



Notes: The charts show the annual provincial nominal GDP shares (in percent of the annual national nominal GDP) in 2012 (the first year of the estimation sample) and 2019 (the last year of the estimation sample), in which the national GDP is the sum of all provincial GDP. Source: National Bureau of Statistics.

3.5 Data Sources

The data for constructing policy variables, outcome variables, and confounding variables are downloaded from NBS, PBoC, National Interbank Funding Center, and Refinitiv Datastream. The list of variables and the corresponding definitions are shown in Appendix 2. The data set includes the data from 2012 Q3 to 2019 Q4 (the "last" four-quarter-ahead GDP growth is the figure in 2020 Q4) and covers 30 provincial administrative units in mainland China (including 22 provinces, 4 municipalities and 4 autonomous regions; Tibet is excluded, as its economic behavior is quite different from other provincial administrative units), while missing data will be filled by linear interpolation and extrapolation. In addition, observations of Hubei during 2019 Q1 to 2019 Q4 (corresponding outcome variables having values from 2020 Q1 to 2020 Q4) are excluded due to more severe impacts from COVID-19 in 2020. In total, the data set has 896 observations.

There are nine confounding variables (Loan_to_Deposit, Share_Business_loans, Share_Exports, Tertiary_industry, Share_small_bank, Share_Shadow_banking, Share_small_firm, Share_SOE, and Coastal) included in the data set. All confounding variables are lagged by one quarter for quarterly data and lagged by one year for annual data to avoid the endogeneity. However, due to the problem of data availability, some variables have an annual frequency. In the data set, the annual series are disaggregated into quarterly series, for which the quarters in the year use the annual figures in the corresponding year.

4 Estimation Results

This section provides the estimation results using causal forest and interpretable machine learning techniques to assess the heterogeneous impacts of China's monetary policy and their determinants (confounding variables). There are six sets of estimation results, consisting of three outcome variables (real GDP growth gaps, CPI inflation gaps, and loan growth gaps) and two different monetary policy stances (monetary easing and monetary tightening) per outcome variable. The monetary policy variables are constructed using the Markov switching Taylor-rule model (equation 1).

4.1 Conditional Average Treatment Effects (CATEs)

First of all, the heterogeneous impacts of monetary policy can be measured by the conditional average treatment effects (CATEs), which are estimated by causal forest. CATEs for the whole sample in all six models are close to zero. Thus, they are consistent with expectations. Since the outcome variables are the gaps in provincial value from the corresponding national average, it is expected that the impacts of monetary policy will be cancelled out among the provinces. Therefore, the CATEs for the whole sample should be close to zero.

However, since the main research question of this paper is about the impacts of monetary policy on provincial economies, assessing CATEs for each province is more meaningful. Figure 4 shows the estimated average impact of monetary policy stances for 30 provinces. In each chart, the provincial CATEs (marked in the "-" symbol) are the average of policy impacts for all observations in the province within the estimation sample. The policy impacts are proxied by the differences between the outcome variables (gaps in economic variables) with the policy against those without the policy. A positive CATE implies that an originally positive gap widens further, while an originally negative gap shrinks. An estimated positive CATE thus means that the province in question scores better in the regional ranking. An estimated negative CATE causes the opposite to happen. Furthermore, a positive (negative) CATE implies a larger (smaller) change in the gap during monetary easing and a smaller (larger) change in the gap during monetary tightening. The confidence intervals with two standard errors are also shown in the charts (the black lines indicate the confidence intervals).

There are 17, 13, and 12 provinces registering larger changes in gaps (positive CATEs) for real GDP growth, CPI inflation growth, and loan growth respectively when there is monetary easing. Meanwhile, monetary tightening causes 18, 13, and 12 provinces to experience larger changes in gaps (negative CATEs) for real GDP growth, CPI inflation growth, and loan growth.

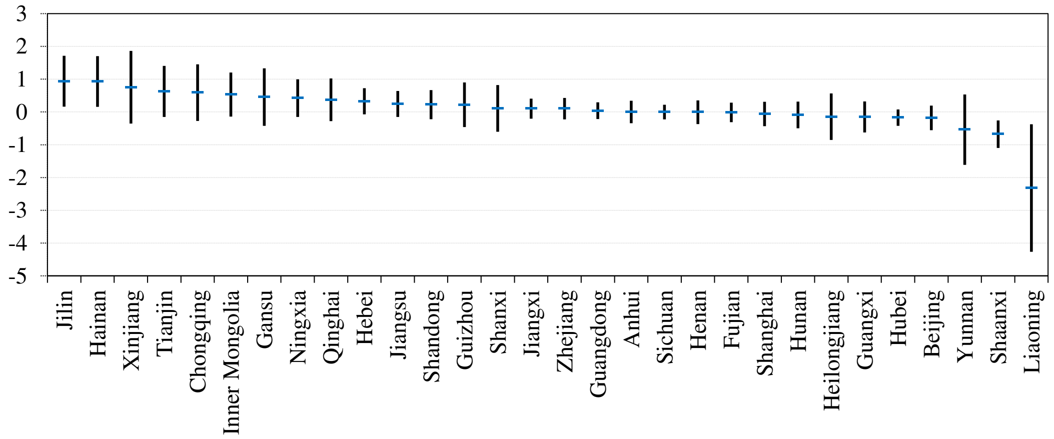
In general, the provinces with larger changes in gaps (positive CATEs) during monetary easing will also have larger changes in gaps (negative CATEs) during monetary tightening, while the impacts are roughly symmetric in two types of monetary policy stances. In addition, the corresponding rankings of provinces for the size of impacts are similar. Specifically, for real GDP growth gaps, the top four largest changes in gaps during monetary easing are Jilin, Hainan, Xinjiang, and Tianjin, and they are also the top four largest changes in gaps during monetary tightening. Conversely, the bottom four (i.e., the smallest changes in gaps) under monetary easing are Liaoning, Shaanxi, Yunnan, and Beijing, and they are also the four smallest changes in gaps under monetary tightening.

Some provinces registered large standard errors, representing larger fluctuations in the outcome variables and/or the confounding variables, which indicates that the fundamental economic variables experienced larger changes during the sample period. For example, Liaoning has the largest standard errors among the provinces for the policy impacts on real GDP growth gaps. Liaoning experienced a sharp drop in real GDP growth during 2015–2017, and the growth rate was particularly lower than that of the other provinces. Liaoning was the major heavy industry base in China, particularly the steel industry, and it had many SOEs. However, in recent decades, the reform in Liaoning's economic structure has been slow, and the fragile steel industry has been hurt by the sharp drop in global commodity prices since 2014.[13]

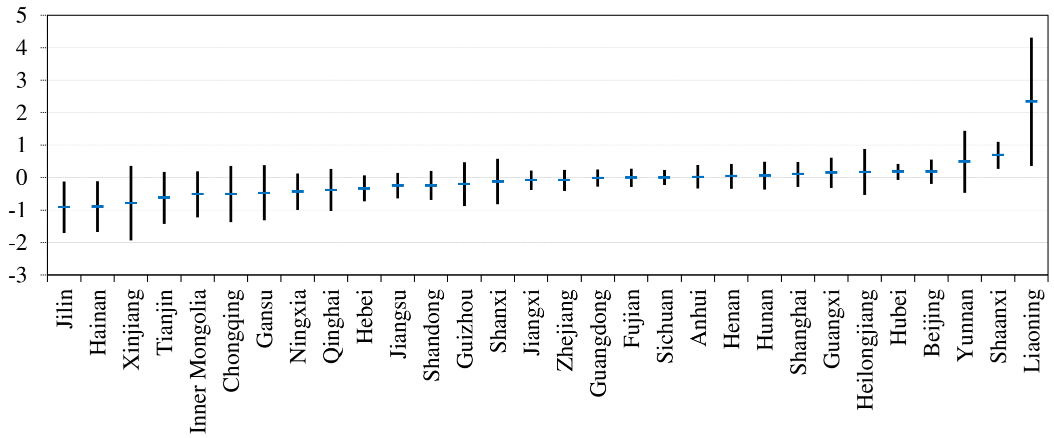
[13] See https://www.ft.com/content/61346c8c-0d09-11e6-b41f-0beb7e589515 and https://www.scmp.com/news/china/economy/article/2104789/liaoning-worst-performer-chinas-northeast-lags-behind-countrys.

Figure 4. Causal Forest Predictions for the Impacts of Monetary Stances

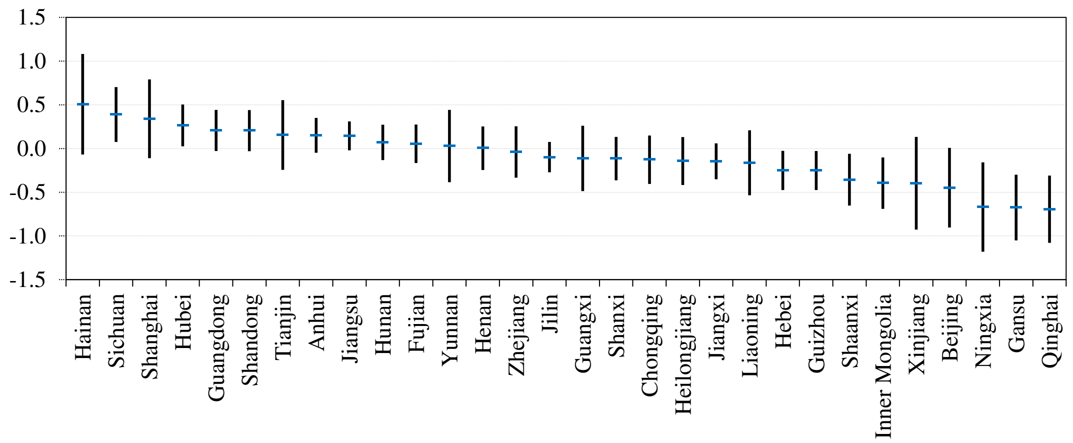
(a) Gaps in Real GDP Growth: Monetary Easing



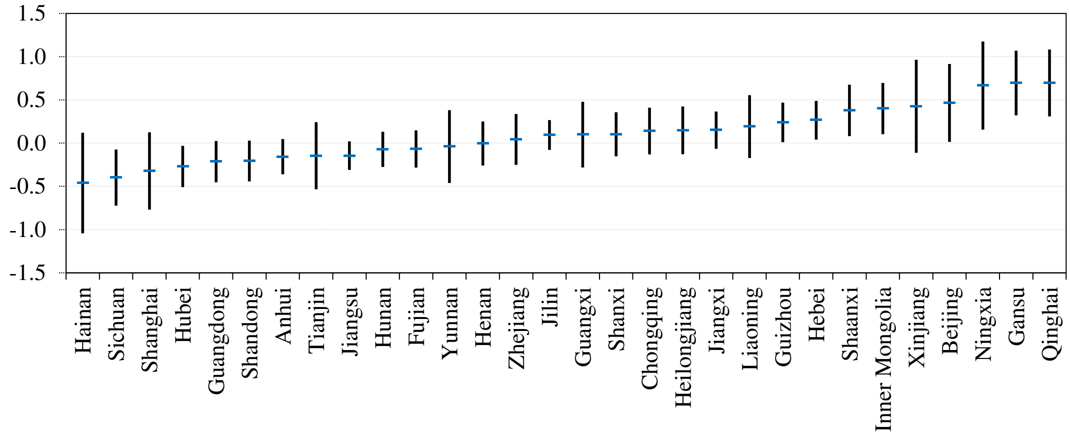
(b) Gaps in Real GDP Growth: Monetary Tightening



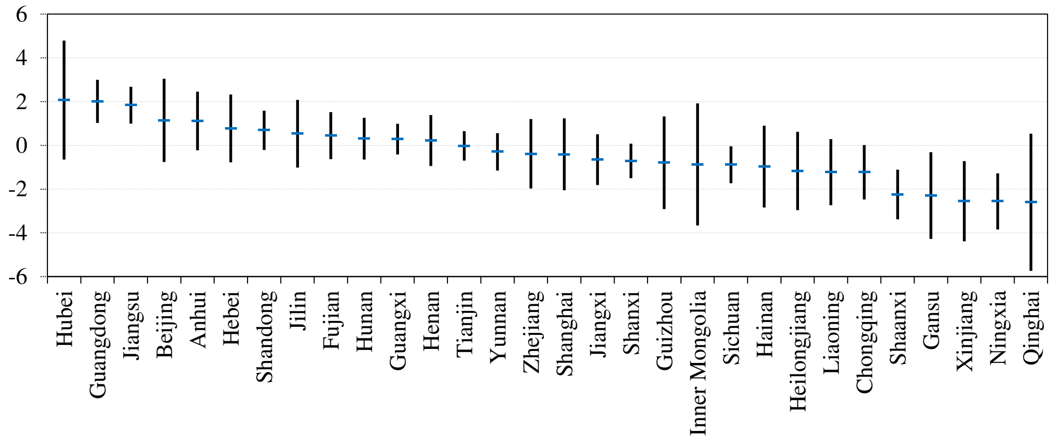
(c) Gaps in CPI Inflation: Monetary Easing



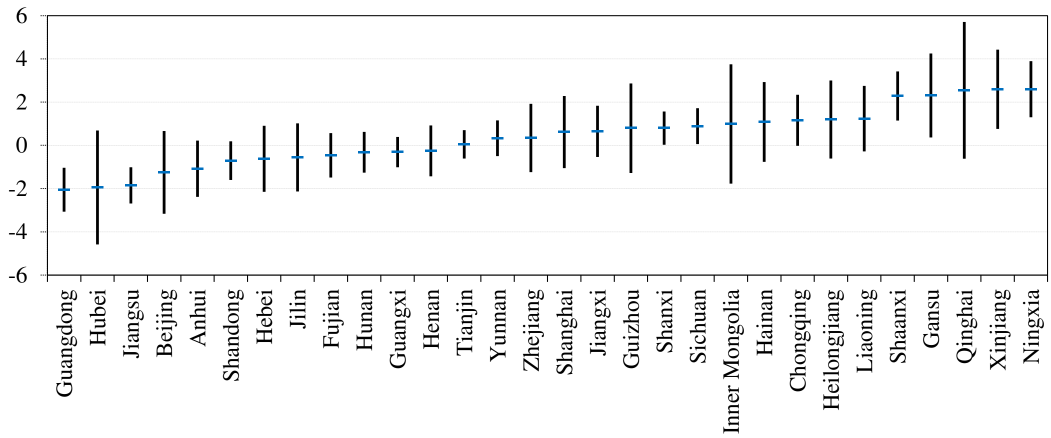
(d) Gaps in CPI Inflation: Monetary Tightening



(e) Gaps in Loan Growth: Monetary Easing



(f) Gaps in Loan Growth: Monetary Tightening



Notes: The blue "-" symbols are the CATEs for the provinces, and the black vertical lines indicate the confidence intervals with two standard errors.

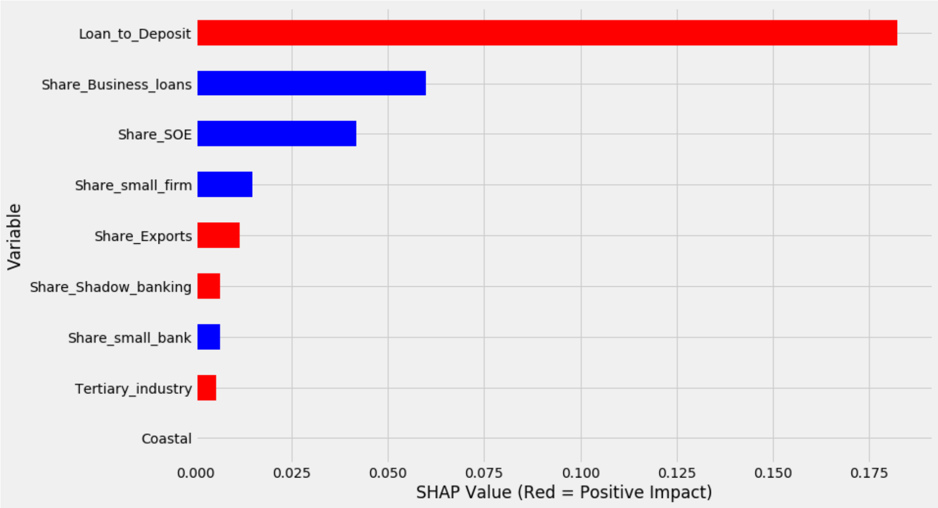
4.2 Variable Importance

After estimating the policy impacts, the interpretable machine learning methods can be used to analyze the contributions of confounding variables to the policy impacts. SHAP analysis is used to discover the importance of the confounding variables. Appendix 3 uses the examples of individual observations to illustrate the importance of the confounding variables on monetary policy impacts by using SHAP waterfall charts. For the individual observation, the 2018 Q4 is selected as an example of monetary easing, and the 2016 Q4 of monetary tightening. The top four (largest changes in gaps during monetary easing and monetary tightening) and bottom four provinces (the smallest changes in gaps during monetary easing and monetary tightening) in real GDP growth gaps are included in Appendix 3, in which the ranking of provinces is based on the ranking of the average policy impacts (CATEs) over the full sample (shown in Figure 4a). Each SHAP waterfall chart shows the contributions of different confounding variables (with the directions of contributions) to the policy impacts on the province at a particular time point, the contribution of which is calculated using SHAP. Using Jilin as an example, the monetary policy would increase changes in real GDP growth gaps in the provinces with higher LTD and, to a lesser extent, a higher share of business loans (positive contributions during monetary easing and negative contributions during monetary tightening). In general, the heterogeneous provincial monetary policy impacts are mainly affected by factors related to the credit channel.

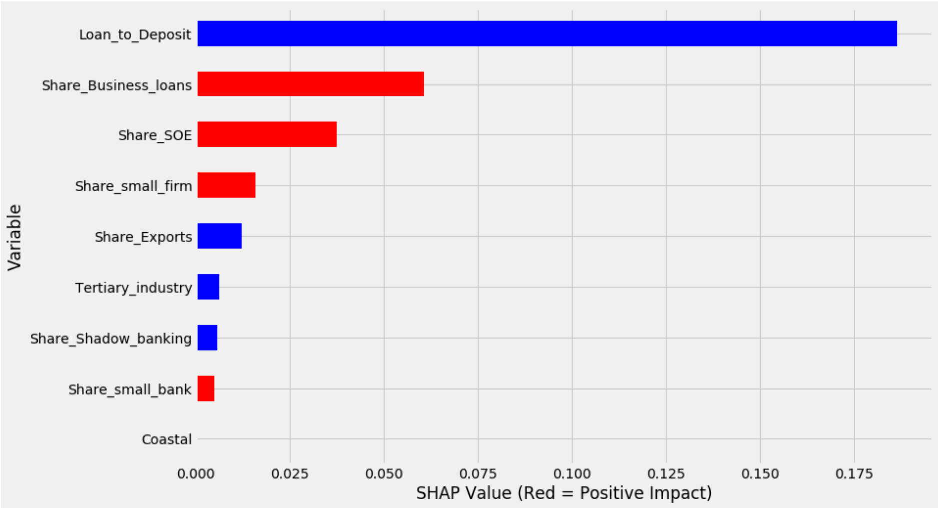
For the full sample, the variable importance (based on SHAP) can be summarized by SHAP variable importance charts. Figure 5 shows the aggregate importance of confounding variables in determining the monetary policy impacts on different outcome variables under different monetary policy stances. The X-axis in the charts shows the sum of absolute Shapley values per confounding variable across the sample. The red (blue) bar represents the positive (negative) contribution to the policy impacts, which enlarges (reduces) changes in gaps during monetary easing but reduces (enlarges) changes in gaps during monetary tightening.

Figure 5. Importance of Confounding Variables (SHAP)

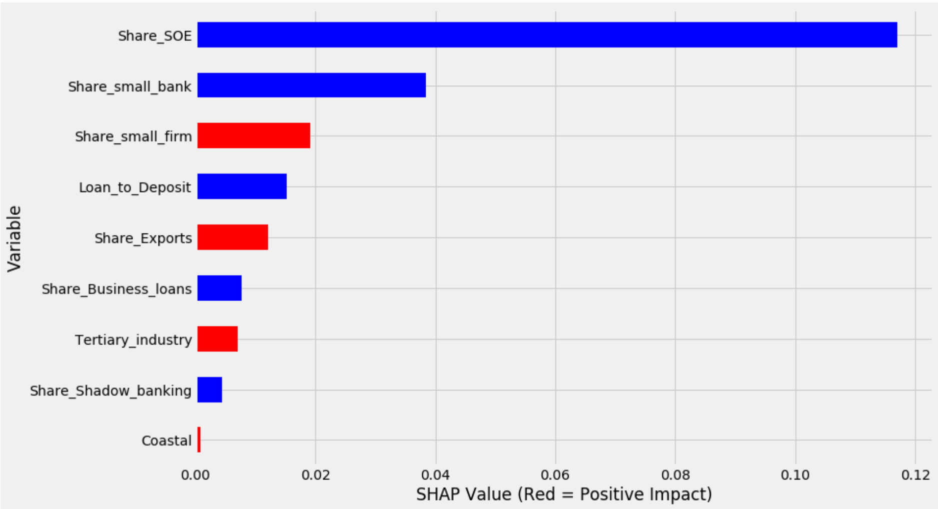
(a) Gaps in Real GDP Growth: Monetary Easing



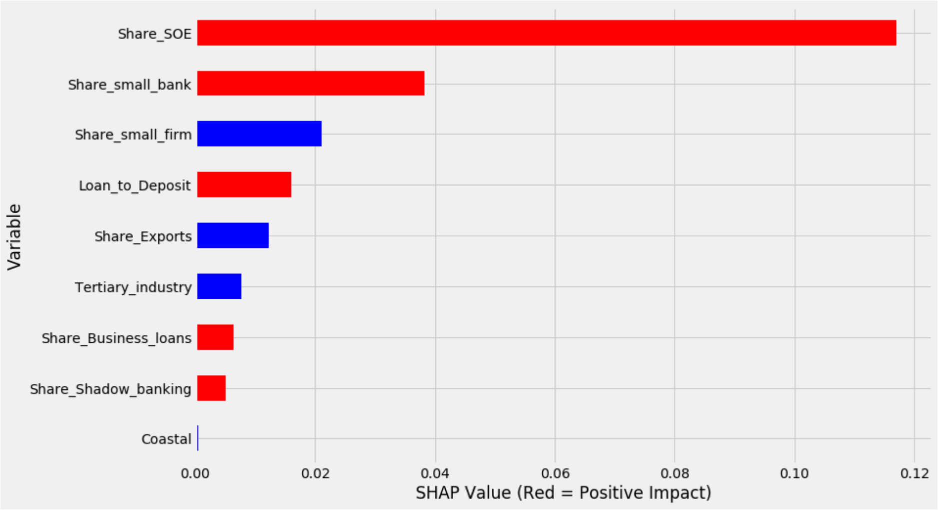
(b) Gaps in Real GDP Growth: Monetary Tightening



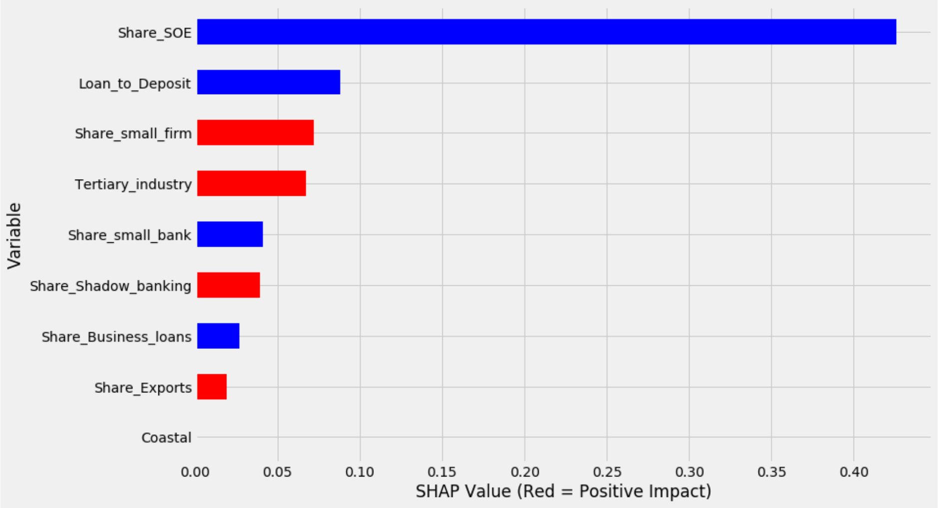
(c) Gaps in CPI Inflation: Monetary Easing



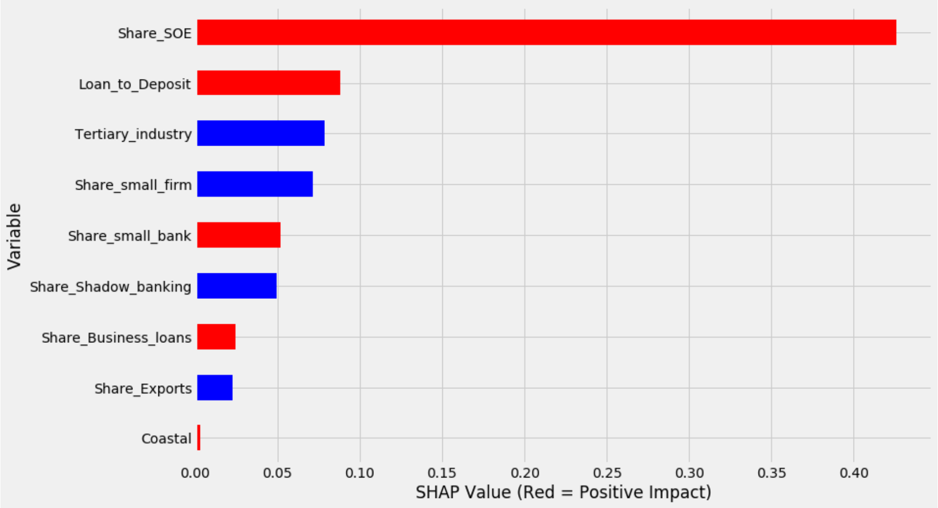
(d) Gaps in CPI Inflation: Monetary Tightening



(e) Gaps in Loan Growth: Monetary Easing



(f) Gaps in Loan Growth: Monetary Tightening



Notes: The charts show the importance of confounding variables based on SHAP analysis (that is, the sum of absolute Shapley values per confounding variable across the sample). The red (blue) bar represents the positive (negative) contribution to the policy impacts.

Starting with the results analyzed by different outcome variables, the monetary policy impacts with the larger changes in real GDP growth gaps mainly come from the higher LTD. The results are symmetric in both monetary easing and monetary tightening. Meanwhile, the impacts will be partly offset by the higher shares of business loans, SOEs, and small firms, as they reduce the changes in gaps caused by monetary policies. These factors are the most important in determining changes in real GDP growth gaps, for which the results suggest that the availability of credit funding and the broad credit channel (credit demand) play major roles. The exchange rate channel (the higher share of exports) is significant but less important than the credit channel, while the interest rate channel (the higher share of tertiary industry) is insignificant.

For CPI inflation gaps, higher shares of SOEs, small banks, and higher LTD are the most important factors that reduce changes in gaps caused by monetary policy. On the other hand, the higher shares of exports and small firms, to a lesser extent, enlarge changes in gaps due to the impacts of monetary policy. Both the broad and narrow credit channels (credit demand and supply) play major roles in determining the monetary policy impacts on CPI inflation gaps. Similar to the policy impacts on real GDP growth gaps, the exchange rate channel (the higher share of exports) is also significant, while the role of the interest rate channel (the higher share of tertiary industry) is limited.

For the loan growth gaps, the most important determinants are higher shares of SOEs, LTD, and shares of a small bank, for which the monetary policy impacts will reduce changes in gaps. Higher shares of small firms and tertiary industry (the role of the interest rate channel) increase the changes in gaps caused by monetary policies. Similar to CPI inflation gaps, both the broad and narrow credit channels (credit demand and supply) play major roles. The role of the interest rate channel (a higher share of tertiary industry) is less important, and the impacts through the exchange rate channel (a higher share of exports) are relatively limited.

After being analyzed with respect to different factors, the results related to variable importance suggest that the credit channel is significant and most important in determining heterogeneous provincial monetary policy impacts. Real GDP growth is mainly affected by the supply of funding, while CPI and loan growth are influenced more by factors related to the demand for credit.

Specifically, the heterogeneous monetary policy impacts mainly came from the different credit channel features in different provinces. For the supply side of the credit channel, a higher level of funding availability (LTD) is most significant for increasing the changes in gaps in real GDP growth with the implementation of the monetary policy. In the meantime, it is less significant in reducing changes in gaps in CPI inflation and loan growth. On the other hand, a higher share of small banks in the banking sector is significant in lowering changes in gaps in CPI inflation, while its effects on lowering changes in gaps in real GDP growth and loan growth are limited.[14] Also, a higher share of business loans is significant in reducing changes in gaps in real GDP growth, while it is less significant in lowering changes in gaps in CPI inflation and loan growth.

For the demand side of the credit channel with respect to the monetary policy impacts, a higher share of SOEs plays the most important role in reducing changes in provincial gaps in CPI inflation and loan growth, but it has mild impacts on lowering changes in gaps in real GDP growth. Meanwhile, the firm's size has an important role in the provincial gaps in CPI inflation and loan growth but a less significant role in the gaps in real GDP growth. Thus, for provinces with a higher share of small firms, implementing monetary policy reduces changes in gaps in real GDP growth but enlarges changes in gaps in CPI inflation and loan growth.[15]

For the remaining confounding variables, the relatively larger impacts through the exchange rate channel can be found on CPI inflation, but such impacts on real GDP growth and loan growth are less significant. A larger share in exports increases changes in all gaps in real GDP growth, CPI inflation, and loan growth.[16] The influence of the interest rate channel on the heterogeneous monetary policy impacts is relatively limited, particularly for real GDP growth and CPI inflation, while a higher share in tertiary industry increases changes in gaps in real GDP growth, CPI inflation, and loan growth.[17] Shadow banking is not significant with respect to importance for all gaps, despite the fact that a higher share of shadow banking increases changes in gaps in real GDP growth and loan growth but reduces changes in CPI inflation gaps. Finally, the regional differential (proxied by the dummy for the coastal region) can be neglected in the sample period.

In general, the variable importance results are consistent with the existing literature. Specifically, Guo and Masron (2017) found that factors relating to the credit channel are the

[14] For a robustness check, if the share of small banks is replaced by the share of large banks, the importance of the variable (with the opposite sign of impacts) is similar.
[15] The results for variable importance are similar if the share of small firms is replaced by the share of large firm (with the opposite sign of impacts).
[16] Similar results occur when the share of exports is replaced by the share of total trades (sum of exports and imports).
[17] As a robustness check, replacing the share of tertiary industry with the share of the secondary industry (i.e., the negative impacts of a higher share in the secondary industry) shows consistent results.

most important ones in determining the heterogeneous regional impacts of China's monetary policy on economic growth. Specifically, both the credit demand (shares of SOEs and small firms) and, to a lesser extent, credit supply (shares of small banks) are significant. For the share of loans to business, Cortes and Kong (2007) found that the share of loans to industrial firms is significant. However, the interest rate channel is insignificant. Different from the existing literature, the location of provinces (dummy for provinces in the coastal region) is not significant in this paper, but it was significant in the studies of Cortes and Kong (2007) and Guo and Masron (2017). The difference could be explained by the different policy focuses in different samples. The existing literature studied the sample from 1978 until 2011, during which time the coastal (eastern) region was the main growth engine of China, and the Chinese authorities emphasized a "get rich first" strategy rather than a balanced growth strategy by 2000. However, this paper studies the sample from 2012 to 2019, when the authorities were concerned more with developing central and western regions.

In addition, for those variables that were not assessed by the existing literature, this paper also finds that the supply of credit is important with respect to the real GDP growth gaps, for which the LTD is most important in determining the regional impacts of monetary policy. The exchange rate channel has not been assessed in the previous literature on regional monetary policy impacts for China. However, empirical results for other countries were mixed (Dominguez-Torres and Hierro, 2019). This paper finds that the exchange rate channel is less important, although the provinces with a high export share show increased changes in gaps in provincial economic growth, inflation, and loan growth that is consistent with expectations. Finally, this paper finds that the importance of shadow banking is limited. The existing literature has only studied the heterogeneous regional impacts of monetary policy on GDP growth. However, this paper also studies the impacts on inflation and loan growth. This paper finds that the factors related to credit channels are the main determinants of the regional impacts on CPI inflation and loan growth. The results are generally consistent with the impacts on regional real GDP growth.

The results for variable importance suggest that the credit channel is the main channel of monetary policy. Specifically, for credit supply, provinces with a high level of funding availability (high LTD) and a high share of small banks would widen the positive gaps in provincial economic growth from the national average.

Meanwhile, as a supplement to the conventional bank loan, credit from shadow banking, including private lending, microcredit, peer-to-peer (P2P) lending, has increased significantly in the last decade (see Chen et al., 2018; Funke et al., 2015, 2019). However, SHAP results suggest that shadow banking is not significant for all outcome variables. This may be because the size of shadow banking varies over time. For example, when there is monetary easing, alternative funding is weaker, but it is strong when there is monetary tightening. Nevertheless, a higher share of shadow banking enlarges the changes in gaps in the provincial economic and loan growth. Therefore, policymakers should be aware that the provinces with a high demand for alternative funding may overreact to changes in the monetary policy stance.

The demand for credit, a higher share of small firms, and a lower share of SOEs and business loans would also widen the positive gaps. The provinces with more diversified economies, i.e., more small firms and small banks but fewer SOEs, could enlarge monetary policy impacts on the gaps in provincial economic variables. Therefore, policymakers should be aware that the national monetary policy may help to promote economic growth and maintain price stability, but the heterogeneous regional impacts can reinforce uneven economic development. Thus, different policymakers should coordinate to search for the optimal fiscal and monetary policy mix.

4.3 Marginal Effects of Confounding Variables

After assessing the importance of confounding variables on the impacts of monetary policy, this subsection uses a PDP to check the numerical values of marginal effects for confounding variables on monetary policy impacts. Appendix 4 presents the PDPs for confounding variables (except the dummy variable for the coastal region), which provides the estimated marginal effects (partial functions) of each confounding variable on different outcome variables under different policy stances.

In each chart of Appendix 4, the X-axis shows the distribution of values of a confounding variable, for which the higher the bar, the more observations with the specific range of that confounding variable. The Y-axis is the predicted treatment effects (the predicted impacts of monetary policy on outcome variables), and the line in the charts shows the predicted treatment effects affected by that confounding variable with a specific range of values. The positive (negative) marginal effects of the specific confounding variables on the policy impacts indicate that the variable enlarges (reduces) changes in gaps during monetary easing but reduces (enlarges) changes in gaps during monetary tightening.

The PDP for the marginal effects of LTD on gaps in real GDP growth during the monetary easing (the chart in the top-left corner of Figure A4.1a in Appendix 4) can be used as an example. The highest bar on the X-axis shows that the largest number of observations have an LTD between 78% and 79%. When the LTD is over 80%, the changes in real GDP growth gaps are larger under monetary easing (positive marginal effects).

Overall, when there is monetary easing, larger changes in real GDP growth gaps (positive marginal effects) are expected with higher LTD (over 80%), larger shares of shadow banking (over 10%), small banks (over 30%), exports (over 40%) and small firms (over 25%), smaller shares of business loans (below 15%) and SOEs (below 20%), as well as a medium-sized tertiary industry (between 50% and 55% of GDP). Similar marginal effects can be found when there is monetary tightening (larger changes in gaps in real GDP growth, with negative marginal effects), except for two confounding variables. Specifically, a larger share of shadow banking (over 10%) reduces changes in gaps more in real GDP growth by 0.3–0.7 percentage points, while a larger share of tertiary industry (over 50%) lowers changes in real GDP growth gaps by over 0.2 percentage points.

Larger changes in gaps in CPI inflation are expected with lower LTD (below 55%), a larger share of small firms (over 30%), smaller shares of business loans (between 10% and 20%), SOEs (below 50%) and small banks (below 13%), and a medium-sized tertiary industry (between 50% and 55% of GDP), when there is monetary easing. In the meantime, shadow banking and exports have negative impacts on the gaps in CPI inflation during monetary easing. A similar pattern of marginal effects (larger changes in gaps) can be found when there is monetary tightening.

When there is monetary easing, provinces are expected to have larger changes in loan growth gaps when they have lower LTD (below 95%), smaller shares of business loans (between 15% and 25%), SOEs (below 45%) and small banks (below 35%), and larger shares of shadow banking (above 10%), tertiary industry (over 55%), exports (over 60%) and small firms (between 26% and 43%). A similar pattern of marginal effects (larger changes in gaps) can be found when there is monetary tightening.

In general, the PDP results are comparable with the SHAP-based variable importance results, and they can provide more specific numerical information. Although monetary policy impacts on outcome variables have similar sources under either monetary easing or monetary tightening, the impacts are smaller under monetary easing. Furthermore, despite some confounding variables not being significant from the results of variable importance, the marginal effects on the impacts of monetary policy could be large when the values of confounding variables exceed some thresholds (like the size of shadow banking). Lastly, the PDP shows that nonlinearities could be found in some confounding variables, for example, monetary policy causes larger changes in real GDP growth gaps with a medium-sized tertiary industry.

5 Conclusions

This paper provides the first machine learning estimation for the heterogeneous regional impacts of monetary policy on different provinces in China. This paper confirms the usefulness of causal machine learning in assessing the regional impacts of monetary policy. In particular, the machine learning methods handle nonlinearities better than traditional econometrics. The PDPs show that the nonlinearities are captured well in the marginal effect analysis. Specifically, the effects of the size of tertiary industry on the monetary policy impacts are not linear with respect to changes in real GDP growth gaps. The marginal effects of tertiary industry on changes in real GDP growth gaps will be the largest when the share of tertiary industry in GDP is between 49%–55%. Beyond this, the effects on changes in real GDP growth gaps become smaller.

The empirical results show that the national monetary policy has heterogeneous provincial impacts, given the divergence in regional development in China. Overall, the impacts of monetary easing and monetary tightening are generally symmetric. For the determinants of heterogeneous regional monetary policy impacts, the factors relating to credit channels are the main factors to determine the impacts of Chinese monetary policy on regional economies. Nevertheless, the role of shadow banking is not as important as expected, while the impacts of changes in economic structure (proxied by the share of tertiary industry) are limited. The importance and marginal effects of determinants on the monetary policy impacts are similar under monetary easing and monetary tightening; however, the marginal effects are generally larger under monetary tightening.

In the process of marketization reform of monetary policy, China has developed a hybrid approach to the monetary policy, which fits the national economy. However, the impacts of the monetary policy in different provinces could be highly heterogeneous due to the divergence of provincial economies, which suggests that China's monetary policy is not a "one-size-fits-all". Nevertheless, the national monetary policy can sharpen the problem of uneven economic development. Therefore, the central bank and other policymakers should coordinate to deliver an optimal mix of fiscal and monetary policies subject to the uneven provincial responses to the single monetary policy.

References

Albuquerque, B. (2019), "One size fits all? Monetary policy and asymmetric household debt cycles in U.S. States", *Journal of Money, Credit and Banking*, Vol. 51 No. 5, pp. 1309–1353.

Athey, S. and Imbens, G. (2017), "The state of applied econometrics: Causality and policy evaluation", *Journal of Economic Perspectives*, Vol. 31 No. 2, pp. 3–32.

Athey, S. and Imbens, G. (2019), "Machine learning methods that economists should know about", *Annual Review of Economics,* Vol. 11, pp. 685–725.

Athey, S., Tibshirani, J. and Wager, S. (2019), "Generalized random forests", *Annals of Statistics*, Vol. 47 No. 2, pp. 1148–1178.

Athey, S. and Wager, S. (2019), "Estimating treatment effects with causal forests: An application", *Observational Studies*, Vol. 5.

Carlino, G. and DeFina, R. (1998), "The differential regional effects of monetary policy", *Review of Economics and Statistics*, Vol. 80 No. 4, pp. 572–587.

Carlino, G. and DeFina, R. (1999), "The differential regional effects of monetary policy: Evidence from the U.S. States", *Journal of Regional Science*, Vol. 39 No. 2, pp. 339–357.

Chakraborty, C. and Joseph, A. (2017), "Machine learning at central banks", *Bank of England Staff Working Paper*, No. 674.

Chen, K., Higgins, P., Waggoner, D.F. and Zha, T. (2016), "China pro-growth monetary policy and its asymmetric transmission", *NBER Working Paper*, No. 22650.

Chen, K., Ren, J. and Zha, T. (2018), "The nexus of monetary policy and shadow banking in China", *American Economic Review*, Vol. 108 No. 12, pp. 3891–3936.

Clarida, R., Galí, J. and Gertler, M. (1998), "Monetary policy rules in practice: Some international evidence", *European Economics Review*, Vol. 42 No. 6, pp. 1033–1068.

Clarida, R., Galí, J. and Gertler, M. (2000), "Monetary policy rule and macroeconomic stability: Evidence and some theory", *Quarterly Journal of Economics*, Vol. 115 No. 1, pp. 147–180.

Cortes, B.S. and Kong, D. (2007), "Regional effects of Chinese monetary policy", *The International Journal of Economic Policy Studies*, Vol. 2, pp. 15–28.

Dominguez-Torres, H. and Hierro, L. (2019), "The regional effects of monetary policy: A survey of the empirical literature", *Journal of Economic Surveys*, Vol. 33 No. 2, pp. 604–638.

Friedman, J.H. (2001), "Greedy function approximation: A gradient boosting machine", *Annals of Statistics,* Vol. 29 No. 5, pp. 1189–1232.

Funke, M., Li, X. and Tsang, A. (2019), "Monetary policy shocks and peer-to-peer lending in China", *BOFIT Discussion Papers*, 23/2019.

Funke, M., Mihaylovski, P. and Zhu, H. (2015), "Monetary policy transmission in China: A DSGE model with parallel shadow banking and interest rate control", *HKIMR Working*

Papers, 12/2015.

Funke, M. and Tsang, A. (2020), "The People's Bank of China's response to the coronavirus pandemic – A quantitative assessment", *Economic Modelling*, Vol. 93, pp. 465–473.

Funke, M. and Tsang, A. (2021), "The direction and intensity of China's monetary policy: A dynamic factor modelling approach," *Economic Record*, Vol. 97 No. 316, pp. 100–122.

Furceri, D., Mazzola, F. and Pizzuto, P. (2019), "Asymmetric effects of monetary policy shocks across US states", *Regional Science*, Vol. 98, pp. 1861–1891.

Georgopoulos, G. (2009), "Measuring regional effects of monetary policy in Canada", *Applied Economics*, 41(16), pp. 2093–2113.

Girardin, E., Lunven, S. and Ma, G. (2017). "China's evolving monetary policy rule: From inflation-accommodating to anti-inflation policy", *BIS Working Paper No*. 641, Basel.

Girotti, M. (2018), "The effects of monetary policy on the composition of bank deposits and on loan supply", *Rue de la Banque* (*Banque de France*), Vol. 59.

Guo, X. and Masron, T.A. (2014), "Regional effects of monetary policy in China—The role of spillover effects", *Asian Academy of Management Journal*, Vol. 19 No. 1, pp. 113–146.

Guo, X. and Masron, T.A. (2017), "Regional effects of monetary policy in China: Evidence from China´s provinces", *Bulletin of Economic Research*, Vol. 69 No. 2, pp. 178–208.

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

Hauptmeier, S., Holm-Hadulla, F. and Nikalexi, K. (2020), "Monetary policy and regional inequality", *ECB Working Paper* No. 2385.

He, Q. (2011), "Dances with Chinese data: Are the reform period Chinese provincial panel data reliable?", *Munich Personal RePEc Archive (MPRA) Paper*, No. 35418.

Horst, M. and Neyer, U. (2019), "The impact of quantitative easing on bank loan supply and monetary policy implementation in the Euro area", *Düsseldorf Institute for Competition Economics (DICE) Discussion Paper*, No. 325.

Kamber, G. and Mohanty, M.S. (2018), "Do interest rates play a major role in monetary policy transmission in China?", *BIS Working Paper*, No. 714, Basel.

Kerola, E. and Mojon, B. (2021), "What 31 provinces reveal about growth in China," *BIS Working Paper*, No. 925, Basel.

Koch-Weser, I.N. (2013), "The reliability of China's economic data: An analysis of national output", *U.S.-China Economic and Security Review Commission Staff Research Project*.

Künzel, S.R., Sekhon, J.S., Bickel, P.J. and Yu, B. (2019), "Metalearners for estimating heterogeneous treatment effects using machine learning", *PNAS*, Vol. 116 No. 10, pp. 4156–4165.

Lundberg, S.M. and Lee, S. (2017), "A unified approach to interpreting model predictions", *Advances in Neural Information Processing Systems (NIPS)*.

Molnar, C. (2019), *Interpretable Machine Learning: A Guide for Making Black Box Models Explainable*, https://christophm.github.io/interpretable-ml-book/.

Molnar C., Casalicchio, G. and Bischl, B. (2020), “Interpretable machine learning – A Brief history, state-of-the-art and challenges”, In: Koprinska, I. et al. (Eds.) *ECML PKDD 2020 Workshops. ECML PKDD 2020. Communications in Computer and Information Science*, Springer, 1323. https://doi.org/10.1007/978-3-030-65965-3_28

Mullainathan, S. and Spiess, J. (2017), “Machine learning: An applied econometric approach”, *Journal of Economic Perspectives*, Vol. 31 No. 2, pp. 87–106.

Pizzuto, P. (2020), “Regional effects of monetary policy in the U.S.: An empirical reassessment”, *Economics Letters*, Vol. 190, 109062.

Shapley, L.S. (1953), “17. A value for n-person games”, In: Kuhn, H.W. and Tucker, A.W. (Eds., 2016) *Contributions to the Theory of Games* (AM-28), Volume II, Princeton University Press, pp. 307–318. https://doi.org/10.1515/9781400881970-018

Sun, R. (2018), “A narrative indicator of monetary conditions in China”, *International Journal of Central Banking*, Vol. 14 No. 4, pp. 1–42.

Tiffin, A. (2019), “Machine learning and causality: The impact of financial crises on growth”, *IMF Working Paper*, WP/19/228.

Wynne, M.A. and Koech, J. (2012), “One-size-fits-all monetary policy: Europe and the U.S.”, *Federal Reserve Bank of Dallas Economic Letter*, Vol. 7 No. 9.

Zheng, T., Wang, X. and Guo, H. (2012), “Estimating forward-looking rules for China’s monetary policy: A regime-switching perspective”, *China Economic Review*, Vol. 23, pp. 47–59.

Appendix 1: List of Provincial Administrative Units Included in the Sample

Table A1.1: Provincial Administrative Units in Mainland China

No.	Name	Type	Region	Coastal Region?
1	Anhui	Province	Central	
2	Beijing	Municipality	East	Yes
3	Chongqing	Municipality	West	
4	Fujian	Province	East	Yes
5	Gansu	Province	West	
6	Guangdong	Province	East	Yes
7	Guangxi	Autonomous Region	West	
8	Guizhou	Province	West	
9	Hainan	Province	East	Yes
10	Hebei	Province	East	Yes
11	Heilongjiang	Province	Northeast	
12	Henan	Province	Central	
13	Hubei	Province	Central	
14	Hunan	Province	Central	
15	Inner Mongolia	Autonomous Region	West	
16	Jiangsu	Province	East	Yes
17	Jiangxi	Province	Central	
18	Jilin	Province	Northeast	
19	Liaoning	Province	Northeast	
20	Ningxia	Autonomous Region	West	
21	Qinghai	Province	West	
22	Shaanxi	Province	West	
23	Shandong	Province	East	Yes
24	Shanghai	Municipality	East	Yes
25	Shanxi	Province	Central	
26	Sichuan	Province	West	
27	Tianjin	Municipality	East	Yes
28	Xinjiang	Autonomous Region	West	
29	Yunnan	Province	West	
30	Zhejiang	Province	East	Yes

Appendix 2: Data Description

Table A2.1. List of Variables

Number	Variable	Description
Outcome variable (*Y*):		
Y1	F4_RGDP_growth_gaps	Four-quarter-ahead of provincial real GDP growth gaps from the national average of real GDP growth (year-on-year (yoy) growth, gaps in percentage points)
Y2	F4_CPI_inflation_gaps	Four-quarter-ahead of provincial CPI inflation gaps from the national average of CPI inflation (yoy inflation rate, gaps in percentage points)
Y3	F4_Loan_growth_gaps	Four-quarter-ahead of provincial loan growth gaps from the national average of loan growth (yoy growth, gaps in percentage points)
Treatment (*W*):		
W1	Ease	Dummy variable for monetary easing periods
W2	Tighten	Dummy variable for monetary tightening periods
Confounding variables (*X*):		
<u>Quarterly data</u>		
Loan-related variables (for credit channel: narrow credit channel [credit supply])		
X1	Loan_to_Deposit	Loan-to-deposit ratio
X2	Share_Business_loans	Share of loans to nonfinancial enterprises and government ***Remark***: 1. The series started in 2015, and the missing data before 2015 are filled in with the average in 2015. 2. Figures for Tianjin, Jilin, and Heilongjiang are proxied by the total loan minus the loans for personal consumption.
Trade-related variables (for exchange rate channel)		
X3	Share_Exports	Share of total exports in GDP
<u>Annual data</u>		
Economic structure variables (for interest rate channel)		
X4	Tertiary_industry	Share of tertiary industry value-added in GDP
Banking variables (for credit channel: narrow credit channel [credit supply])		
X5	Share_small_bank	Share of bank assets held by small and medium-sized banks (including urban commercial banks and rural financial institutions)
X6	Share_Shadow_banking	Increases in total social financing other than bank loans in a share of the outstanding amount of total bank loans ***Remark***: 1. The annual data are used, as the quarterly series is too volatile. 2. The series started in 2013, and the missing data before 2013 are filled in with the average in 2013.
Firm type variables (for credit channel: broad credit channel [credit demand])		
X7	Share_small_firm	Share of industrial firm assets held by small and medium-sized firms
X8	Share_SOE	Share of industrial firm assets held by SOEs
Regional dummy variables		
X9	Coastal	Dummy for the coastal region

<u>Notes:</u> There are 896 observations (from 2012 Q3 to 2019 Q4), excluding Hubei in 2019 Q1 to 2019 Q4 and all observations from Tibet. The alternative variables are highlighted in grey. All confounding variables are lagged by one quarter for quarterly data and lagged by one year for annual data to avoid endogeneity.

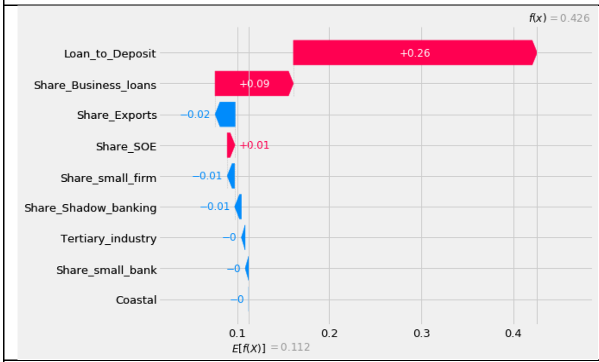
Appendix 3: SHAP Waterfall Charts for Selected Observations

Figure A3.1. SHAP Waterfall Charts

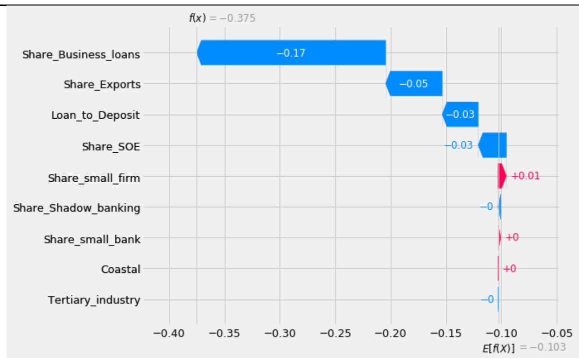
(a) Gaps in Real GDP Growth: Top 4 Provinces

Monetary Easing (2018 Q4)	Monetary Tightening (2016 Q4)

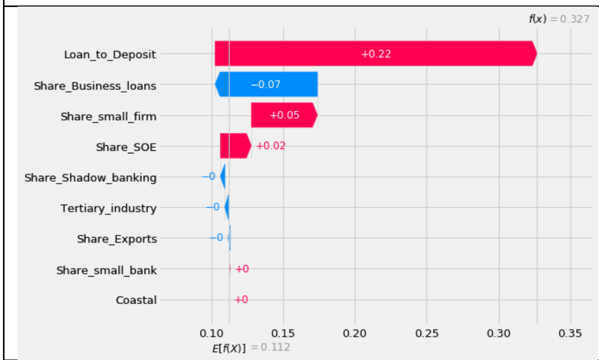
Jilin (Monetary Easing, 2018 Q4)



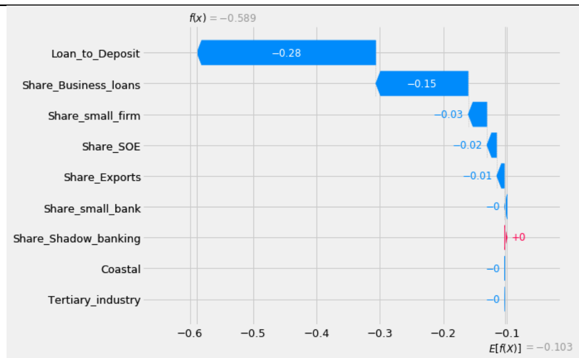
Jilin (Monetary Tightening, 2016 Q4)



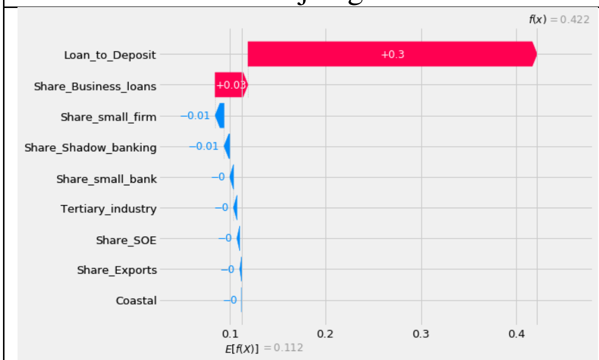
Hainan (Monetary Easing, 2018 Q4)



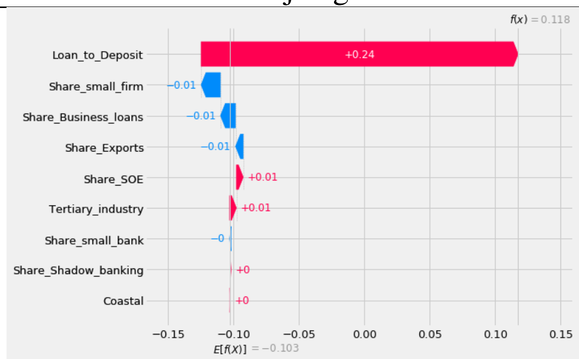
Hainan (Monetary Tightening, 2016 Q4)



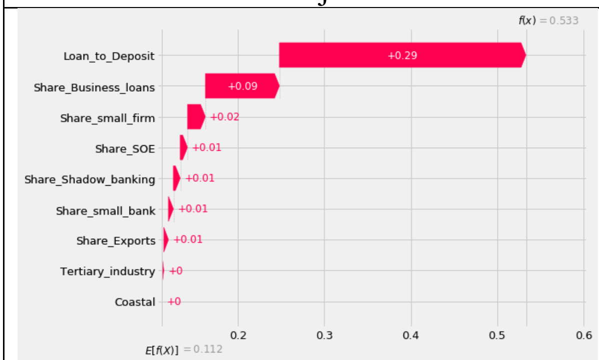
Xinjiang (Monetary Easing, 2018 Q4)



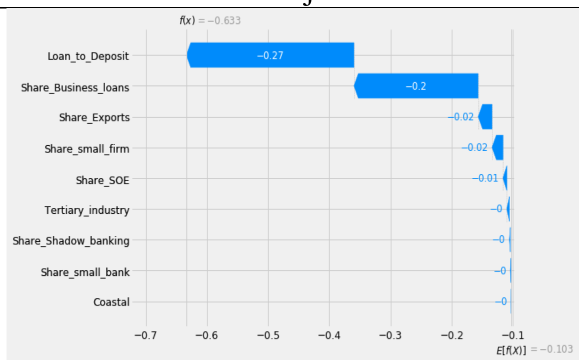
Xinjiang (Monetary Tightening, 2016 Q4)



Tianjin (Monetary Easing, 2018 Q4)



Tianjin (Monetary Tightening, 2016 Q4)



(b) Gaps in Real GDP Growth: Bottom 4 Provinces

Notes: The top four (with the largest changes in gaps during monetary easing) and bottom four provinces (with the smallest changes in gaps during monetary easing) are pricked by using the ranking of the provincial average policy impacts (CATEs) over the full sample (Figure 4a). Each chart shows the contributions of different confounding variables. Red (blue) bar represents the positive (negative) contribution to the policy impacts.

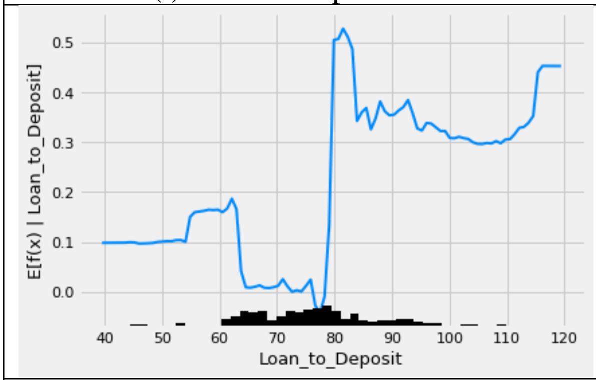
Appendix 4: Marginal Effects of Confounding Variables (PDPs)

Figure A4.1. PDPs

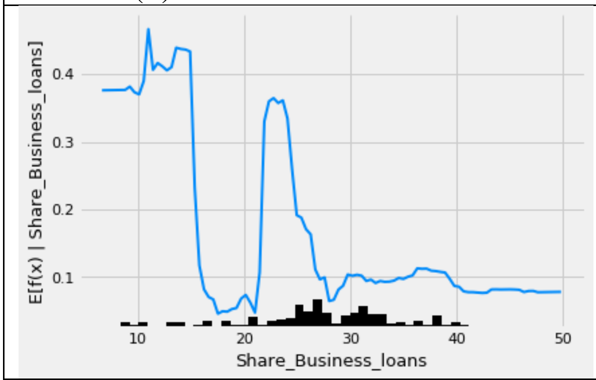
(a) Gaps in Real GDP Growth

Monetary Easing

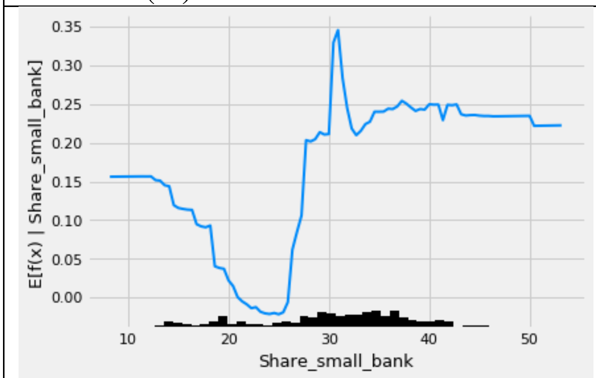
(i) Loan-to-deposit ratio



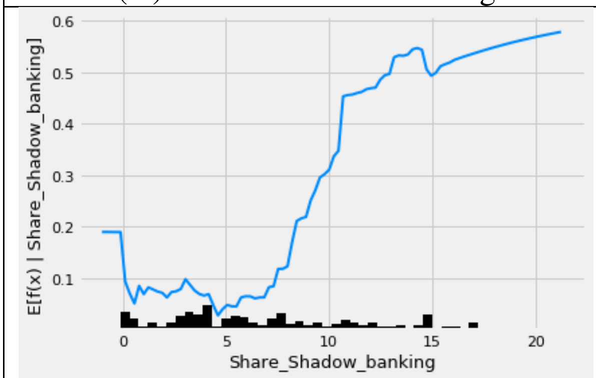
(ii) Share of business loans



(iii) Share of small banks

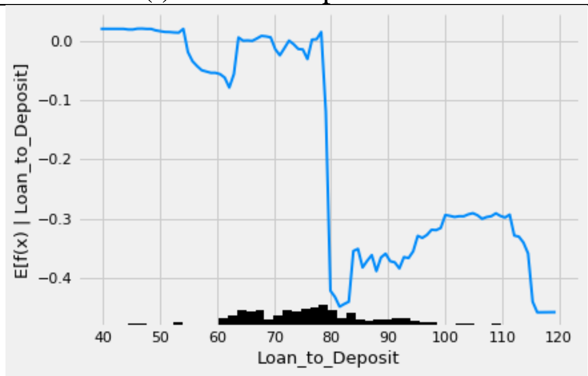


(iv) Share of shadow banking



Monetary Tightening

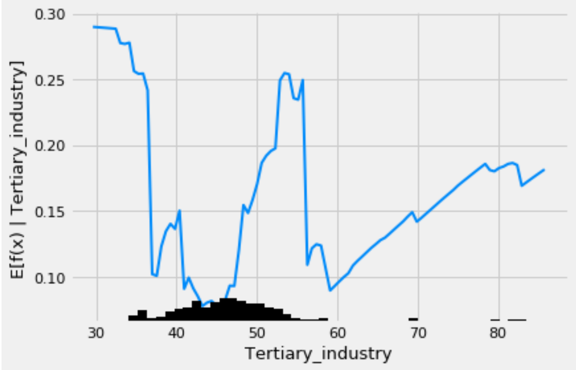
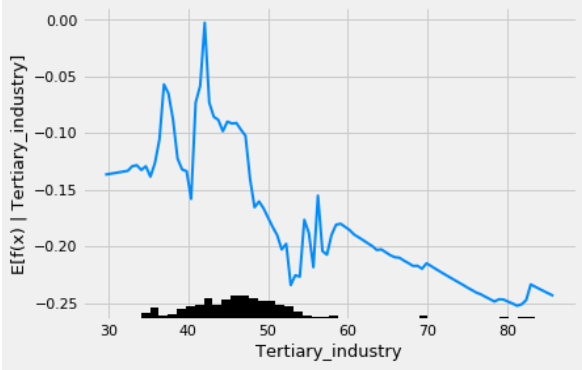
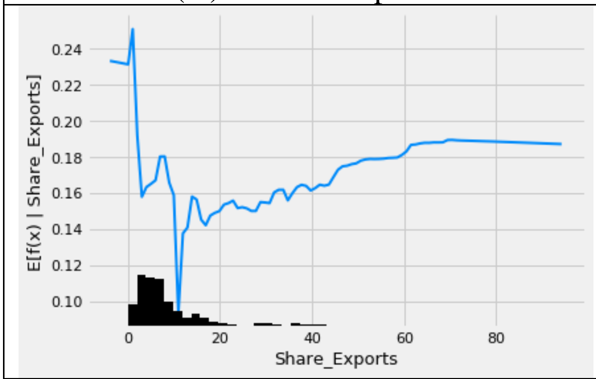
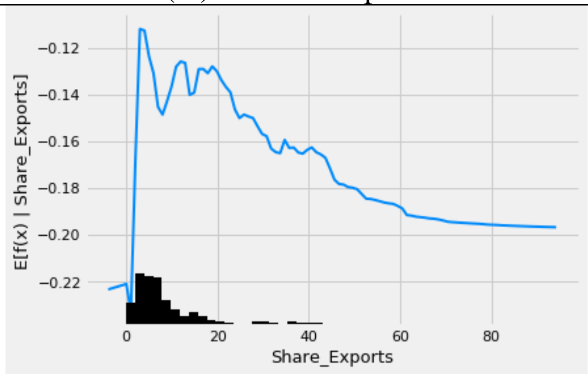
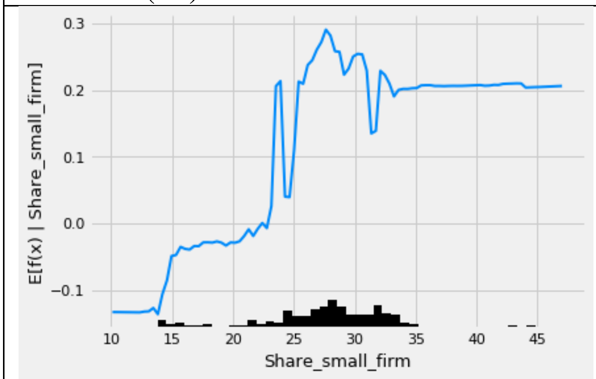
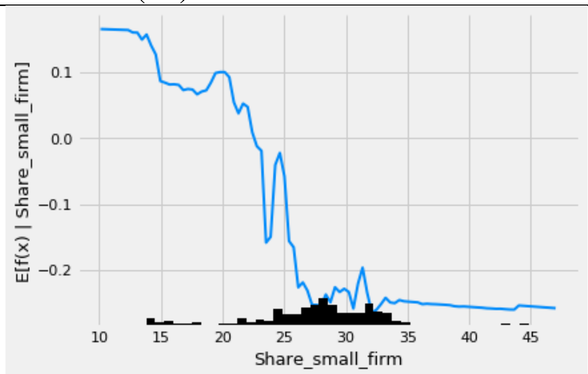
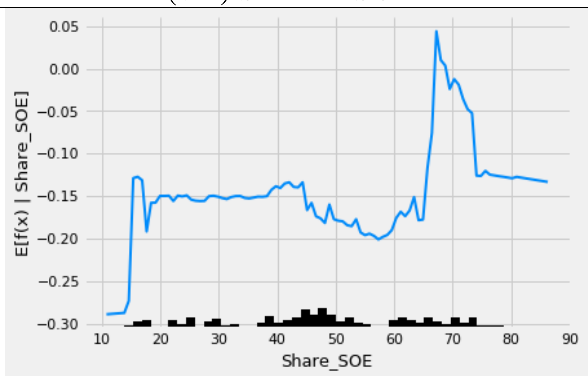
(i) Loan-to-deposit ratio



(ii) Share of business loans

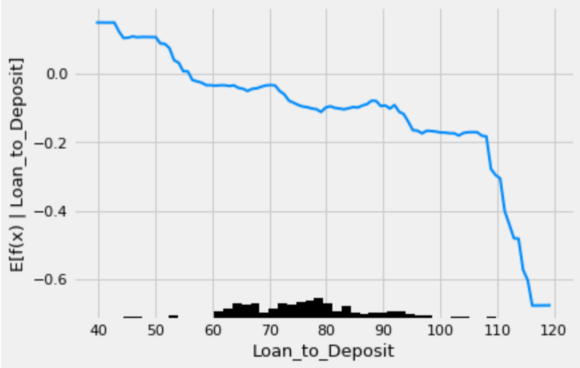
(iii) Share of small banks

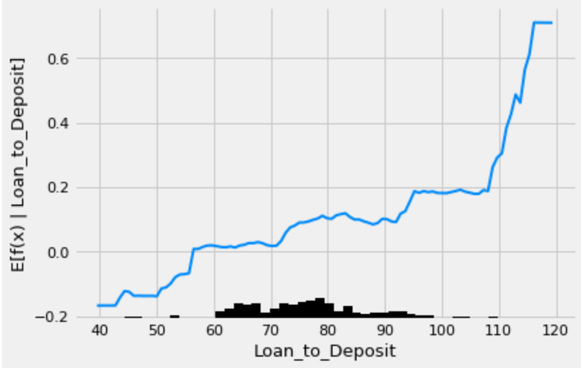
(iv) Share of shadow banking

(v) Share of tertiary industry	(v) Share of tertiary industry
	
(vi) Share of exports	(vi) Share of exports
	
(vii) Share of small firms	(vii) Share of small firms
	
(viii) Share of SOEs	(viii) Share of SOEs
	

(b) Gaps in CPI Inflation

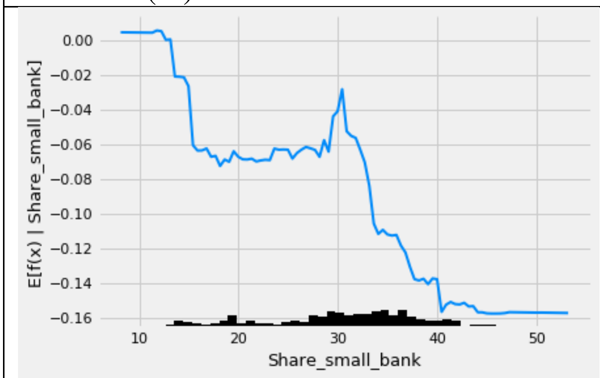
Monetary Easing	**Monetary Tightening**
(i) Loan-to-deposit ratio	(i) Loan-to-deposit ratio





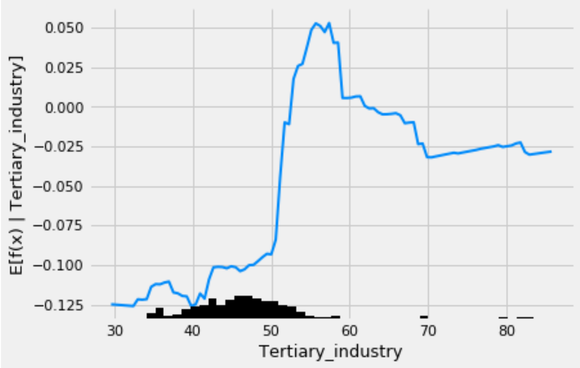
(ii) Share of business loans	(ii) Share of business loans

(iii) Share of small banks	(iii) Share of small banks

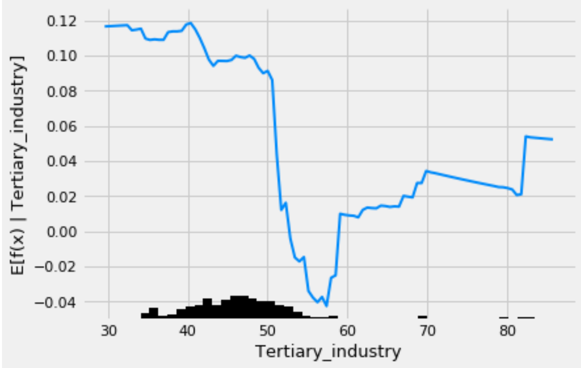


(iv) Share of shadow banking	(iv) Share of shadow banking

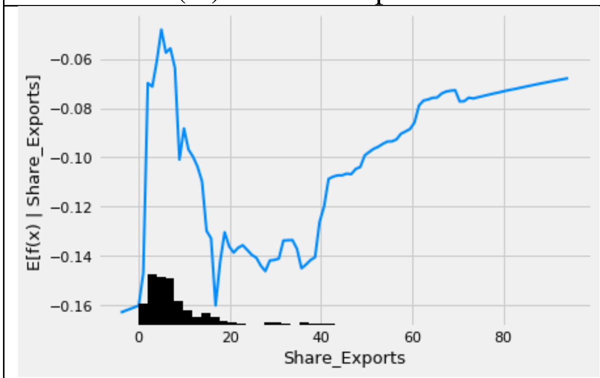
(v) Share of tertiary industry



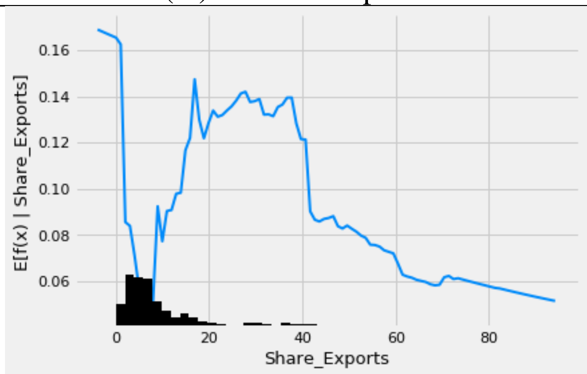
(v) Share of tertiary industry



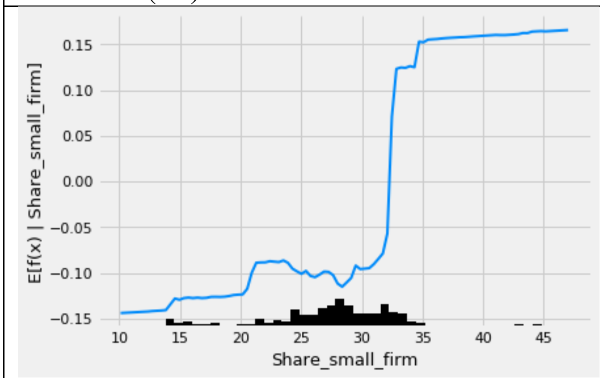
(vi) Share of exports



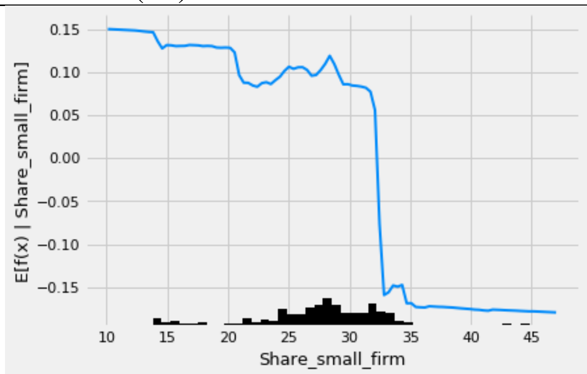
(vi) Share of exports



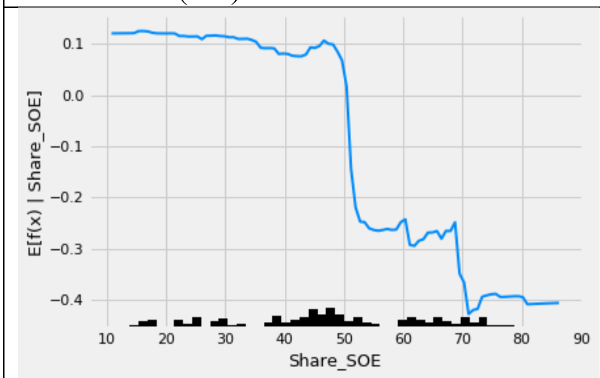
(vii) Share of small firms



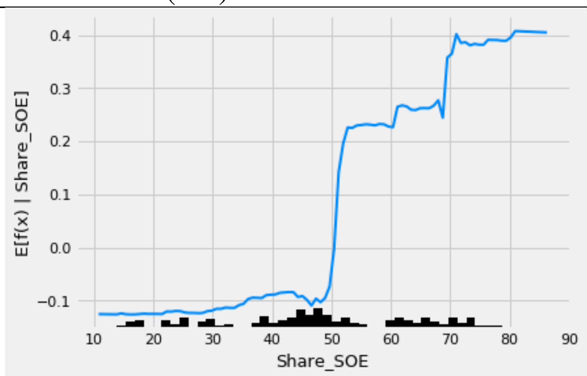
(vii) Share of small firms



(viii) Share of SOEs

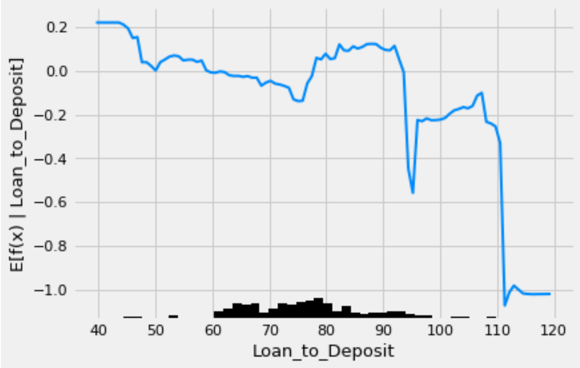


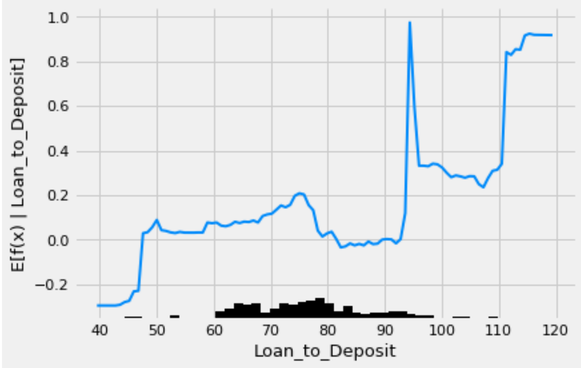
(viii) Share of SOEs



(c) Gaps in Loan Growth

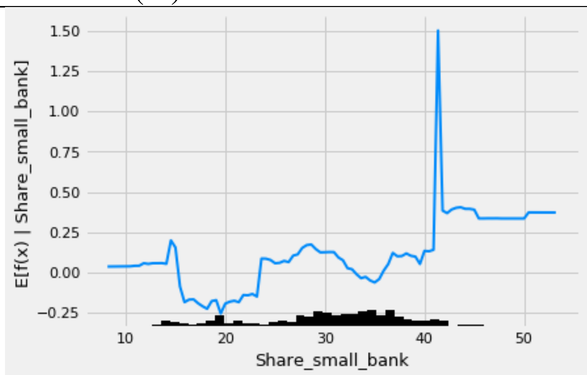
Monetary Easing	**Monetary Tightening**
(i) Loan-to-deposit ratio	(i) Loan-to-deposit ratio



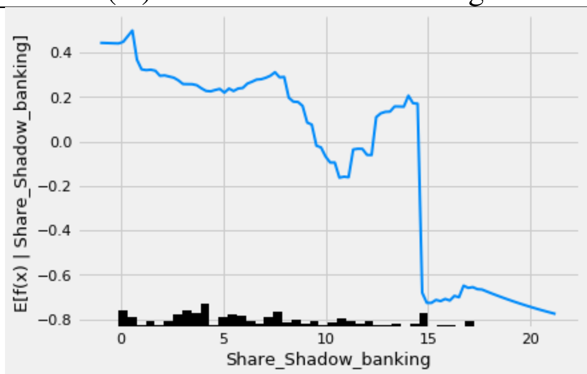


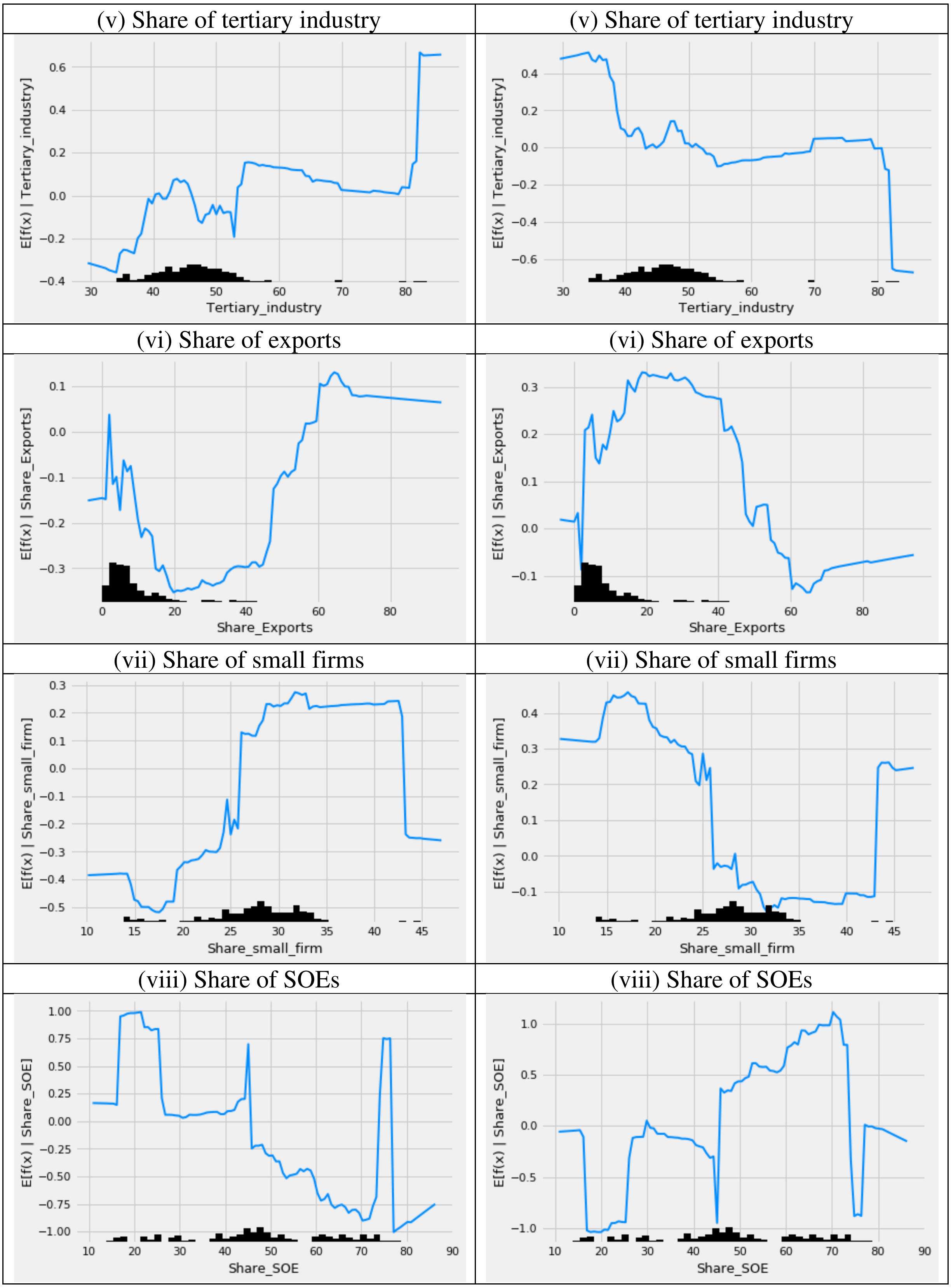
(ii) Share of business loans	(ii) Share of business loans

(iii) Share of small banks	(iii) Share of small banks



(iv) Share of shadow banking	(iv) Share of shadow banking





Notes: The marginal effects (partial functions) of confounding variables on the predicted policy impacts are shown in the PDPs. PDPs for the dummy variable for the coastal region have been skipped because it is insignificant (see Figure 5).