Quantile Policy Effects: An Application to US Macroprudential Policy

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August 11, 2023

Abstract

To assess the dynamic distributional impacts of macroeconomic policy, we propose quantile policy effects to quantify disparities between the quantiles of potential outcomes under different policies. We first identify quantile policy effects under the unconfoundedness assumption and propose an inverse probability weighting estimator. We then examine the asymptotic behavior of the proposed estimator in a time series framework and suggest a blockwise bootstrap method for inference. Applying this method, we investigate the effectiveness of US macroprudential actions on bank credit growth from 1948 to 2017. Empirically, we find that the effects of macroprudential policy on credit growth are asymmetric and depend on the quantiles of credit growth. The tightening of macroprudential actions fails to rein in high credit growth, whereas easing policies do not effectively stimulate bank credit growth during low-growth periods. These findings suggest that US macroprudential policies might not sufficiently address the challenges of soaring bank credit or ensure overarching financial stability.

Keywords: Causal effects; Impulse response functions; Macroprudential policy; Propensity score; Quantile functions

1 Introduction

Since the global financial crisis, economists have renewed their interest in the consequences of credit expansions. Recent work has shown that excess credit growth increases financial risk and severely affects the real economy, including in the form of housing market crashes, banking crises, and economic recessions (e.g., Mian and Sufi, 2009; Schularick and Taylor, 2012; Jordà, Schularick, and Taylor, 2013). In the main, central banks and regulators rely on macroprudential policy to address these risks, control credit growth, and maintain stability, with studies focusing on specific countries examining the effects of these policies on bank credit. For example, Elliott, Feldberg, and Lehnert (2013) develop a US credit policy index and note that tightening reduces bank credit, but easing has a limited impact, and Zdzienicka et al. (2015) indicate transient effects. Monnet (2014) combines the narrative approach and discusses credit controls in France. Elsewhere, Aikman, Bush, and Taylor (2016) create a credit policy index for the UK revealing strong effects on bank credit. Kim and Oh (2020) offer results suggesting that macroprudential policy strongly affected household bank loans in Korea after the 1997 Asian financial crisis.

Numerous empirical studies also examine cross-country experiences to assess the effectiveness of macroprudential policy in controlling bank credit growth. For example, Claessens, Ghosh, and Mihet (2013) find that macroprudential policy limits credit growth and mitigates increases in bank leverage for 2,800 banks in 48 countries. Bruno, Shim, and Shin (2017) focus on 12 Asia-Pacific economies and find that tightening macroprudential policy successfully reduces credit growth when reinforcing monetary tightening rather than when it acts in the opposite direction. Using a sample of 119 countries, Cerutti, Claessens, and Laeven (2017) and Cizel et al. (2019) find that macroprudential policies significantly reduce bank credit growth, and policy effectiveness depends on the type of country, whereas Akinci and Olmstead-Rumsey (2018) show that tightening policies reduce bank and housing credit growth across 57 advanced and emerging countries. Recently, Richter, Schularick, and Shim (2019) use the local projection technique and suggest that macroprudential policy lowers real household and mortgage credit in 56 countries.

In addition, several studies examine whether the effect of macroprudential policy varies across the credit growth phase. Claessens, Ghosh, and Mihet (2013) find that macroprudential policy reduces the growth of bank leverage and assets in boom times, whereas, in downturns, the effect depends on the type of macroprudential policy. McDonald (2015) reveals that tightening actions exert a more considerable impact when credit expands quickly in 17 economies, and easing actions could then be more effective during downturns. Cerutti, Claessens, and Laeven (2017) also find that macroprudential policy works poorly during busts. Lastly, Jiménez et al. (2017) argues that dynamic provisioning in Spain in 2000 halted a credit boom and served as a bad-times buffer. Together, these studies investigate the relationship between policy influences and past credit growth, rather than gauging their potential in mitigating upcoming financial boom–bust cycles. Consequently, they may not fully illuminate the extent to which macroprudential policy could be adept at steering future financial cycles.

The extant literature highlights a few critical considerations in evaluating macroprudential policy effectiveness. First, we need to estimate the causal effects of the actual and counterfactual reactions of a policy to judge policy effectiveness. Second, we must acknowledge that the effects of macroprudential policy are not instantaneous, but instead permeate through the economy over time. This temporal factor is of interest to fiscal authorities and central bankers, underscoring the importance of the dynamic impacts of policy. Third, our focus should shift from average to distributional effects when assessing policy effectiveness across the various stages of credit growth. For example, policymakers may be more interested in a policy's impact on extreme quantiles of bank credit growth rates as these represent financial boom and bust cycles. An effective macroprudential policy would then influence the right tail of credit growth through tightening actions. At the same time, easing efforts should have a more pronounced effect on the left tail or lower quantiles.

Regarding the first two points, Angrist and Kuersteiner (2011) and Angrist, Jordà, and Kuersteiner (2018) have expanded the average treatment effect concept to a dynamic average policy effect, thereby accommodating multiple policy choices within a time series framework. The dynamic causal effects in Angrist, Jordà, and Kuersteiner (2018) measure the difference between the average value of the potential outcomes at different forecast horizons.[1] Addressing the third point, White, Kim, and Manganelli (2015) propose a multivariate regression quantile model, which they use to trace the effect on the conditional quantile function over time. Lee, Kim, and Mizen (2021) utilize the structural vector autoregression method to estimate the impact of structural shocks on the entire conditional distribution of the observable structural variables, and Chavleishvili and Manganelli (2017) characterize quantile impulse response functions as the difference between the expected quantile dynamics with and without structural shocks. Nonetheless, the vector autoregression model may lead to biased estimation if the model is misspecified. As the forecast horizon extends, this bias intensifies, potentially presenting a misleading picture to central banks when evaluating policy impacts.

To address the three points at once, this paper proposes quantile policy effects (QPE) to evaluate the effectiveness of macroprudential policy on bank credit growth and the financial cycle. QPE, by quantifying shifts in the distribution of potential outcomes resulting from policy changes, facilitates an exploration of policy effects across various quantiles of potential outcomes. They thus provide a more detailed understanding than possible with only average effects. This is because QPE over time represent the dynamic causal effects on the distributions of the potential outcomes or the impulse responses of policy. They, therefore, offer the complete dynamic causal effects of macroeconomic policy and thus complement the average policy effect in Angrist, Jordà, and Kuersteiner (2018). Assuming unconfoundedness, we identify QPE and introduce an inverse probability weighted estimator, as conceptualized by Firpo (2007), Cattaneo (2010), and Donald and Hsu (2014).[2] We thus contribute to the literature by extending the asymptotic results of the QPE estimator from a cross-sectional framework to a time series framework and by providing a blockwise bootstrap method for inference.

[1]Several studies apply this approach to assess the impact of policies or events. See e.g., Forbes and Klein (2015), Forbes, Fratzscher, and Straub (2015), Jordà, Schularick, and Taylor (2016), and Acemoglu et al. (2019).

[2]Frölich and Melly (2013) and Hsu, Lai, and Lieli (2022) employ the instrumental variable method to develop estimators for unconditional quantile treatment effects without the conditional independence assumption.

To render a causal interpretation for our QPE, we discuss how the framework of Angrist, Jordà, and Kuersteiner (2018) can be expressed as the direct potential outcome system of Rambachan and Shephard (2021) by introducing a structural model of the outcome variable. We also provide sufficient conditions for the structural model such that the unconfoundedness assumption holds. In addition, our work quantifies the policy effect without relying on a specific macroeconomic model, distinguishing it from the quantile vector autoregression approach embraced by White, Kim, and Manganelli (2015), Lee, Kim, and Mizen (2021), and Chavleishvili and Manganelli (2017).

Our empirical study utilizes this proposed method to examine whether macroprudential policy can mitigate high bank credit risk or stimulate low bank credit growth. We focus on monthly data from the US spanning the period from 1948 to 2017 to evaluate the impact of three macroprudential actions (tightening, easing, and unchanging) on bank credit growth, with the unchanging action serving as our counterfactual benchmark policy. We compute QPE at various quantiles of credit growth and across different time horizons to evaluate the responses of bank credit growth to macroprudential actions. Our empirical results reveal the asymmetric impact of macroprudential policy on credit growth, contingent on both the policy actions and the credit growth quantiles. We also conduct thorough robustness checks and sensitivity analyses to ensure the reliability of our findings. In particular, the QPE estimates increase across all quantiles one year after a tightening action. At the 0.9-th quantile, they even turn positive, suggesting that tightening actions may unexpectedly fuel high credit growth, and thereby potentially amplifying financial market risk a year after policy enforcement. The responses remain significantly positive even two years later at the highest quantiles of credit growth. At lower credit growth quantiles, easing actions can further depress already low sector growth. This adverse effect becomes significant 18 months post-implementation. These results highlight the nuanced effects of macroprudential policies on varied credit growth levels, underscoring potential risks. Our findings raise concerns about the effectiveness of these policies in mitigating credit market vulnerabilities.

The remainder of the paper is structured as follows. Section 2 defines QPE and their estimation and discusses asymptotic theory and bootstrap techniques of the proposed estimators. Section 3 investigates the effectiveness of macroprudential policy on bank credit growth using the proposed method. Section 4 concludes. The separate supplementary appendix includes the sensitivity analyses and proofs for all the lemmas and theorems.

2 The Quantile Policy Effect

This section presents the model within a time series framework and defines QPE. We demonstrate that QPE are identifiable under the assumption of unconfoundedness. To estimate QPE, we propose an inverse probability weighting method, incorporating a parametric specification for the policy propensity score. Further, we analyze the asymptotic properties of the proposed estimator and offer a blockwise bootstrap approach for conducting inference.

2.1 Model Framework

We first introduce the model based on Angrist, Jordà, and Kuersteiner (2018) and then discuss how this model representation relates to the direct potential outcome system in Rambachan and Shephard (2021). An observed vector stochastic process can characterize the economy denoted as $\chi_t = (Z_t^{'}, Y_t, D_t^{'})^{'}$. In this representation, Y_t refers to an outcome variable that researchers are interested in. The vector Z_t represents a vector of predetermined variables before time t, also known as covariates, and Z_t is of k_z dimensions with $k_z < \infty$. We allow Z_t to include lagged outcome variables, but not lagged policy variables. Let D_t represent the policy variable with values drawn from the set $\mathcal{D} = \{d_0, ..., d_J\}$. In line with the approach taken by Angrist, Jordà, and Kuersteiner (2018), the realized policy variable D_t is determined by a combination of observed and unobserved variables, as captured by the relationship $D_t = D(Z_t, \psi, \varepsilon_t)$. Let ψ represent a vector of parameters associated with the policy regime, taking values in a parameter space Ψ. Finally, let ε_t denote the policymakers' idiosyncratic information or taste variables, which are not observable.

Following Angrist and Kuersteiner (2011) and Angrist, Jordà, and Kuersteiner (2018), we define $Y_{t,h}^{\psi}(d)$ as the potential outcome for $d \in \mathcal{D}$. Subsequently, the observed outcomes Y_{t+h} are equal to $Y_{t,h}^{\psi}(d)$ if D_t is equal to d. This relationship can be expressed as:

$$Y_{t+h} = \sum_{d \in \mathcal{D}} Y_{t,h}^{\psi}(d) \cdot \mathbf{1}\{D_t = d\}. \tag{1}$$

In Equation (1), the indicator function $\mathbf{1}\{D_t = d\}$ ensures that the potential outcome $Y_{t,h}^{\psi}(d)$ is included in the summation only if D_t is equal to d.

In policy evaluation, it is essential to assess the distributional impacts of policies beyond their average effects. To capture these impacts, we introduce the distribution function for $Y_{t,h}^{\psi}(d_j)$ defined as:

$$F_j^h(q, \psi) = P(Y_{t,h}^{\psi}(d_j) \leq q),$$

where j represents all possible policy choices within the set $\{0, \cdots, J\}$, and ψ is fixed in the parameter space Ψ. This distribution function $F_j^h(q, \psi)$ calculates the probability that the potential outcome $Y_{t,h}^{\psi}(d_j)$ is less than or equal to a given value q. To analyze the distribution further, we can examine specific quantiles. Let τ be a quantile within the interval $(0, 1)$. We define the quantile function $Q_j^h(\tau, \psi)$ for $\tau \in (0, 1)$ of the distribution function $F_j^h(q, \psi)$ as follows:

$$Q_j^h(\tau, \psi) = \inf\{q : F_j^h(q, \psi) \geq \tau\}.$$

The quantile function identifies the lowest value q for which the distribution function exceeds or equals τ.

To quantify the QPE at the τ quantile, we calculate the difference between specific quantiles of potential outcomes under policies d_j and d_0 as follows:

$$\Delta_j^h(\tau, \psi) = Q_j^h(\tau, \psi) - Q_0^h(\tau, \psi).$$

This estimand bears a resemblance to the quantile treatment effect discussed in Firpo (2007), Cattaneo (2010), and Donald and Hsu (2014). However, our approach is uniquely suited for analyzing time series data and conducting macroeconomic policy evaluation. The premise of QPE lies in leveraging the estimands of the distribution function for potential outcomes to derive quantile processes associated with differences between specific quantiles of potential outcomes up to the time horizon H.

QPE thus serve as a quantile-based counterpart to the average policy effect introduced by Angrist and Kuersteiner (2011) and Angrist, Jordà, and Kuersteiner (2018), wherein we replace Y_{t+h} with the indicator function $\mathbf{1}\{Y_{t+h} \leq q\}$. Moreover, QPE allow us to assess the quantile impulse responses to the policy shock, enabling the evaluation of policy effects across the entire time horizon H. Therefore, if policymakers prioritize understanding of the distributional impacts or effects on the tails of the outcome distribution, QPE offer a comprehensive analysis of policy effectiveness. By considering quantiles, QPE provide valuable insights into policy impacts beyond average effects, making it a valuable tool for policymakers and researchers alike.

2.2 Identification

Potential outcomes for counterfactual policy choices are inherently unobserved, posing a challenge for identifying QPE without additional conditions. We introduce the unconfoundedness assumption into our framework to address this and to facilitate identification.

Assumption 1 *(Unconfoundedness) $Y^{\psi}_{t,h}(d_j) \perp D_t | Z_t$ for all $h \geq 0$ and for all d_j, with ψ fixed, $\psi \in \Psi$.*

The unconfoundedness assumption, also referred to as the selection-on-observables assumption or the conditional independence assumption, requires that conditional on observable variables, the policy assignment is independent of the potential outcomes for all horizons $h \geq 0$. In other words, there should be no systematic relationship between the policy choice and the potential outcomes after accounting for the observed variables. A sufficient condition for Assumption 1 is that ε_t is independent of the potential outcomes and Z_t.

We introduce the policy propensity score denoted as $p^j(Z_t, \psi) = P(D_t = d_j | Z_t)$, which represents the conditional probability of selecting policy choice d_j given the observed variables Z_t. The policy propensity score measures the likelihood of policy assignment based on the observed characteristics.

Assumption 2 *(Overlap) The propensity score function* $p^j(Z_t,\psi) > 0$ *for all* Z_t *and for all* $j \in \{0,\cdots,J\}$. *In addition,* $\sum_{j=0}^{J} p^j(Z_t,\psi) = 1$ *for all* Z_t.

Assumption 2, commonly referred to as the overlap assumption, plays a crucial role in identification. It ensures that, for any given values of the observed covariates, there exists a positive probability of observing each policy choice $j \in \{0,\cdots,J\}$. In other words, the overlap assumption guarantees sufficient variation in the observed covariates across different policy choices. This assumption assumes sufficient overlap exists in the distribution of observed covariates across all policy choices.

The following lemma demonstrates the identification of the distribution function of potential outcomes, $F_j^h(q,\psi)$, using the observed data under Assumptions 1 and 2.

Lemma 1 *(Identification of distribution functions) Suppose Assumptions 1 and 2 hold. The distribution function* $F_j^h(q,\psi)$ *can be identified by the observed data as*

$$F_j^h(q,\psi) = E\left[\frac{\mathbf{1}\{D_t = d_j\}\cdot\mathbf{1}\{Y_{t+h} \le q\}}{p^j(Z_t,\psi)}\right].$$

Lemma 1 establishes the identification of the distribution functions for potential outcomes. Given the identification of the distribution functions, the identification of quantile functions for the potential outcomes and the QPE follow directly. This lemma serves as a fundamental basis for estimating and comprehending the quantiles of potential outcomes, enabling the estimation of the QPE.

2.3 Our Framework and the Direct Potential Outcome System

Our model can be considered as a reduced form of a structural model under additional assumptions. We provide a structural model that is a special case using the direct potential outcome system from Rambachan and Shephard (2021) so that our QPE can have a causal interpretation. We also provide sufficient conditions for the identification result in the structural model.

Recall that Z_t are the covariates at time t that could include lagged outcome variables and lagged policy variables. We further let $Z_t = (Z_{y,t}', Z_{e,t}')'$ in which $Z_{y,t}$ is a vector of lagged outcome variables and $Z_{e,t}$ is a vector of exogenous variables. $\{Z_{e,t}\}_{t=1}^{\infty}$ is assumed to be causally unaffected by the assignment process $\{D_t\}_{t=1}^{\infty}$, called a background process in Rambachan and Shephard (2021). Let the outcome variable and the policy variable be generated as the following:

$$Y_t = Y(D_t, Z_t, u_t), \quad D_t = D(Z_t, \psi, \varepsilon_t), \tag{2}$$

where u_t and ε_t denote unobserved variables. The potential outcome variable is then given as $Y_t(d) = Y(d, Z_t, u_t)$. We note that given that $Y_t = Y(D_t, Z_t, u_t)$, it is straightforward to see that Y_t depends on contemporaneous assignment and does not depend on future assignments. It is possible that Y_t depends on past assignments implicitly. For example, suppose that $Z_t = Z_{y,t} = Y_{t-1}$, then it follows that

$$\begin{aligned} Y_t = Y(D_t, Y_{t-1}, u_t) &= Y(D_t, Y(D_{t-1}, Y_{t-2}, u_{t-1}), u_t) \\ &= Y(D_t, Y(D_{t-1}, Y(D_{t-2}, Y_{t-3}, u_{t-2}), u_{t-1}), u_t) = \dots . \end{aligned}$$

Through forward iteration, we can see that Y_t would depend on D_s for all $1 \leq s \leq t$. Similar to Example 3 in Rambachan and Shephard (2021), we have that $(D_1, \dots, D_t)$ only impacts Y_t through D_t directly and through $(Y_1, \dots, Y_{t-1})$ indirectly. In sum, when Z_t includes a lagged outcome variable, Y_t will depend on contemporaneous assignments and past assignments. Under such a structural framework, we can see that our model can be expressed as a direct potential outcome system. Note that according to Rambachan and Shephard (2021), $Y_{t,h}^{\psi}(d)$ is the time-$(t+h)$ potential outcome at the assignment process $(D_1, \dots, D_{t-1}, d, D_{t+1}, \dots, D_{t+h})$.

In the following, we impose conditions on the structural model such that Assumption 1, which is the unconfoundedness assumption, will hold. Then, it follows that QPE can be identified.

Assumption 3 *(Structural Model) Assume that*

1. *Y_t and D_t are generated according to (2);*

2. *$\{\varepsilon_t\}_{t=1}^{\infty}$ and $\{u_t\}_{t=1}^{\infty}$ are sequences of i.i.d. random variables;*

3. $\{\varepsilon_t\}_{t=1}^{\infty}$, $\{u_t\}_{t=1}^{\infty}$ *and* $\{Z'_{e,t}\}_{t=1}^{\infty}$ *are jointly independent.*

Lemma 2 *If Assumption 3 holds, Assumption 1 holds.*

2.4 Estimation

Following the identification result in Lemma 1, the estimation of $F_j^h(q,\psi)$ can be conducted using a two-step procedure. Following the methodology of Angrist and Kuersteiner (2011) and Angrist, Jordà, and Kuersteiner (2018), to accurately estimate $F_j^h(q,\psi)$, in the first step, we estimate the policy regime, denoted as $\hat{\psi}$, and the policy propensity score, denoted $p^j(Z_t,\psi)$ using a parametric model, such as the logit, probit, multinomial logit, or multinomial probit model. As highlighted in Angrist, Jordà, and Kuersteiner (2018), this approach does not define or estimate structural innovations for the policy process. More specifically, in the empirical section of this paper, $p^j(Z_t,\hat{\psi})$ represents the parametric estimate of the policy propensity score. In the second step, the estimation of $F_j^h(q,\psi)$ is accomplished using inverse probability weighting, utilizing the estimated policy propensity score obtained in the first step. The estimation is given by:

$$\hat{F}_j^h(q,\hat{\psi}) = \sum_{t=1}^{T} \frac{\mathbf{1}\{D_t = d_j\} \cdot \mathbf{1}\{Y_{t+h} \leq q\}}{p^j(Z_t,\hat{\psi})} \Bigg/ \sum_{t=1}^{T} \frac{\mathbf{1}\{D_t = d_j\}}{p^j(Z_t,\hat{\psi})},$$

where the weights on each observation are normalized such that the sum of weights is equal to 1, following the approach in Imbens (2004) and Donald and Hsu (2014).

The estimator of the quantile function $Q_j^h(\tau,\psi)$ for $\tau \in (0,1)$ is defined as:

$$\hat{Q}_j^h(\tau,\hat{\psi}) = \inf\{q : \hat{F}_j^h(q,\hat{\psi}) \geq \tau\},$$

where $\hat{F}_j^h(q,\hat{\psi})$ represents the estimated distribution function. Consequently, the estimator for QPE denoted as $\Delta_j^h(\tau,\psi)$ is given by:

$$\hat{\Delta}_j^h(\tau,\hat{\psi}) = \hat{Q}_j^h(\tau,\hat{\psi}) - \hat{Q}_0^h(\tau,\hat{\psi}),$$

where $\hat{Q}_0^h(\tau,\hat{\psi})$ is the estimator of the quantile function for the control group at the same quantile level, τ.

2.5 Asymptotic Properties

Before delving into the asymptotic properties of the QPE estimators, we impose additional regularity conditions in addition to the unconfoundedness assumption.

Assumption 4 *(Weak dependence of the data) The stationary sequence χ_t is β-mixing with $\beta_i = O(i^{-q})$ and $q > p/(p-2)$ for some $2 < p < \infty$.*

Assumption 5 *Assume that the parameter $\psi \in \Psi$ where $\Psi \subset \mathbb{R}^{k_\psi}$ is a compact set and the number of covariates $k_\psi < \infty$.*

Assumption 6 *(Parametric Propensity Scores) Assume that for all $j \in \{0, \cdots, J\}$,*

1. *$E[\mathbf{1}\{D_t = d_j\}|Z_t] = p_t^j(Z_t, \psi_0)$, and for all $\psi \neq \psi_0$, $E[\mathbf{1}\{D_t = d_j\}|Z_t] \neq p^j(Z_t, \psi)$;*

2. *for all Z_t, $p^j(Z_t, \psi)$ is differentiable with respect to ψ for $\psi \in N_\delta(\psi_0) \equiv \{\psi \in \Psi | \|\psi - \psi_0\| \leq \delta\}$ and some $\delta > 0$;*

3. *let $g^j(Z_t, \psi) = 1/p^j(Z_t, \psi)$. $E[\sup_{\psi \in N_\delta(\psi_0)} |g^j(Z_t, \psi_0)|^\varepsilon] \leq M$, $E[\sup_{\psi \in N_\delta(\psi_0)} \|\partial g^j(Z_t, \psi_0)/\partial\psi\|^\varepsilon] \leq M$ and $E[\sup_{\psi \in N_\delta(\psi_0)} \|\partial^2 g^j(Z_t, \psi)/\partial\psi\partial\psi'\|^\varepsilon] \leq M$ with $M < \infty$ and for some $2 < \varepsilon < \infty$.*

Assumption 7 *(Asymptotic properties of $\hat{\psi}$) $\sqrt{T}(\hat{\psi} - \psi_0) = T^{-1/2} \sum_{t=1}^T \ell(D_t, Z_t, \psi_0) + o_p(1)$ with $E[\|\ell(D_t, Z_t, \psi_0)\|^p] < \infty$, where p is the same as in Assumption 4.*

Assumption 8 *For all $h \geq 0$ and $j \in \{0, \cdots, J\}$,*

1. *$Y_{t,h}^\psi(d_j)$ has convex and compact supports $[q_j^l, q_j^u]$;*

2. *$F_j^h(q, \psi)$ is a continuous function on $[q_j^l, q_j^u]$.*

Assumption 4 is derived from Theorem 2.5 of Radulović (2002) and serves as a foundation for applying the empirical process result by Arcones and Yu (1994) and the blockwise bootstrap result by Radulović (2002). Assumptions 5, 6, and 7 share similarities with Conditions 3, 4, and 6, respectively, in Angrist, Jordà, and Kuersteiner (2018). Assumption 7 assumes the existence of an estimator for ψ_0 that is asymptotically normal and has an influence function representation. This assumption is not overly restrictive because, under appropriate low-level conditions, a maximum likelihood estimator for ψ_0 would satisfy Assumption 7. Assumption 8 is similar to Assumption 3.1 in Donald and Hsu (2014). The following theorem establishes the limiting distribution of $\hat{F}_j^h(q, \hat{\psi})$.

Theorem 1 *(Asymptotic properties of $\hat{F}_j^h(q, \hat{\psi})$) Suppose that Assumptions 1–8 hold. Then,*

$$\sqrt{T}(\hat{F}_{\cdot}^h(\cdot, \hat{\psi}) - F_{\cdot}^h(\cdot, \psi_0)) \Rightarrow \mathcal{F}(\cdot, \cdot),$$

where $\Rightarrow$ denotes weak convergence, and $\mathcal{F}(\cdot, \cdot)$ is a mean-zero Gaussian process with covariance functions,

$$\Omega^{\mathcal{F}}((d_{j_1}, q_1), (d_{j_2}, q_2)) = \lim_{T\to\infty} T^{-1} E\left[\left(\sum_{t=1}^{T} w_{t,d_{j_1}}(q_1, \psi_0)\right)\left(\sum_{t=1}^{T} w_{t,d_{j_2}}(q_2, \psi_0)\right)'\right],$$

where

$$\begin{aligned} w_{t,d_j}(q, \psi_0) =& \big(\mathbf{1}\{Y_{t+h} \le q\} - F_j^h(q, \psi_0)\big)\mathbf{1}\{D_t = d_j\} \cdot g^j(Z_t, \psi_0) \\ &+ E\Big[\big(\mathbf{1}\{Y_{t+h} \le q\} - F_j^h(q, \psi_0)\big)\mathbf{1}\{D_t = d_j\} \cdot \frac{\partial g^j(Z_t, \psi_0)}{\partial \psi'}\Big]\ell(D_t, Z_t, \psi_0), \end{aligned}$$

and $g^j(Z_t, \psi_0) = 1/p^j(Z_t, \psi_0)$.

Theorem 1 establishes the weak convergence of the distribution function estimator $\hat{F}_j^h(q, \hat{\psi})$. This theorem resembles Theorem 3.6 in Donald and Hsu (2014), with the key distinction being that we account for weakly dependent data. To establish the asymptotic properties of the quantile process, we impose conditions on the density functions of the potential outcomes. Let $f_h^{\psi}(q, d_j)$ represent the density functions corresponding to the potential outcomes $Y_{t,h}^{\psi}(d_j)$, for all $\{j = 0, \cdots, J\}$. These density functions play a crucial role in analyzing the behavior of the quantile process and its asymptotic properties.

Assumption 9 *For all $h \ge 0$ and $j \in \{0, \cdots, J\}$, $f_h^{\psi}(q, d)$ is continuous and bounded away from 0 on $[q_j^l, q_j^u]$.*

Assumption 9 bears similarity to Assumption 3.7 in Donald and Hsu (2014) and ensures that $F_j^h(q, \psi_0)$ is strictly increasing on the interval $[q_j^l, q_j^u]$, thereby ensures that the quantile function $Q_j^h(\tau,\psi_0)$ is well-defined over the range $(0,1)$. To estimate the complete quantile functions at the parametric rate, it is necessary for the density function $f_h^{\psi}(q,d)$ to be bounded away from 0 on its support. Consequently, this assumption excludes scenarios with unbounded support.[3] The subsequent theorems provide a summary of the limiting behaviors of $\hat{Q}_j^h(\tau,\hat{\psi})$ and $\hat{\Delta}_j^h(\tau,\hat{\psi})$.

Theorem 2 *(Asymptotic properties of $\hat{Q}_j^h(\tau,\hat{\psi})$) Suppose that Assumptions 1–9 hold. Then,*

$$\sqrt{T}(\hat{Q}_{\cdot}^h(\cdot,\hat{\psi}) - Q_{\cdot}^h(\cdot,\psi_0)) \Rightarrow \mathcal{Q}(\cdot,\cdot),$$

where $\mathcal{Q}(\cdot,\cdot)$ is a mean-zero Gaussian process with covariance functions,

$$\Omega^{\mathcal{Q}}((d_{j_1},\tau_1),(d_{j_2},\tau_2)) = \lim_{T\to\infty} T^{-1} E\left[\left(\sum_{t=1}^{T} w_{t,d_{j_1}}^{Q}(\tau_1,\psi_0)\right)\left(\sum_{t=1}^{T} w_{t,d_{j_2}}^{Q}(\tau_2,\psi_0)\right)'\right],$$

where

$$w_{t,d_j}^{Q}(\tau,\psi_0) = -\frac{w_{t,d_j}(Q_j^h(\tau,\psi_0),\psi_0)}{f_h^{\psi}(Q_j^h(\tau,\psi_0),d_j)},$$

with $w_{t,d_j}(\cdot,\psi)$ defined in Theorem 1.

Theorem 2 is derived by applying the functional delta method to the distribution estimators. This method allows us to establish the asymptotic properties of the estimators. The subsequent theorem presents the asymptotic properties of the QPE estimators, shedding light on their behavior in large samples.

Theorem 3 *(Asymptotic properties of $\hat{\Delta}_{\cdot}^h(\cdot,\hat{\psi})$) Suppose that Assumptions 1–9 hold. Then,*

$$\sqrt{T}(\hat{\Delta}_{\cdot}^h(\cdot,\hat{\psi}) - \Delta_{\cdot}^h(\cdot,\psi_0)) \Rightarrow \mathcal{R}(\cdot,\cdot),$$

where $\mathcal{R}(\cdot,\cdot)$ is a mean-zero Gaussian process with covariance functions,

$$\Omega_j^{\mathcal{R}}((d_{j_1},\tau_1),(d_{j_2},\tau_2)) = \lim_{T\to\infty} T^{-1} E\left[\left(\sum_{t=1}^{T} w_{t,d_{j_1}}^{\Delta}(\tau_1;\psi_0)\right)\left(\sum_{t=1}^{T} w_{t,d_{j_2}}^{\Delta}(\tau_2;\psi_0)\right)'\right],$$

where

$$w_{t,d_j}^{\Delta}(\tau;\psi_0) = -\left[\frac{w_{t,d_j}(Q_j^h(\tau,\psi_0),\psi_0)}{f_h^{\psi}(Q_j^h(\tau,\psi_0),d_j)} - \frac{w_{t,d_0}(Q_0^h(\tau,\psi_0),\psi_0)}{f_h^{\psi}(Q_0^h(\tau,\psi_0),d_0)}\right],$$

with $w_{t,d_j}(\cdot,\psi)$ defined in Theorem 1.

[3] However, even in cases with unbounded support, it is still possible to estimate the quantile function $Q_j^h(\tau,\psi_0)$ for $t\in[\epsilon,1-\epsilon]$ for any $0<\epsilon<1/2$, where the density function $f_h^{\psi}(q,d)$ remains bounded away from 0.

2.6 Blockwise Bootstrap

The covariance function becomes intricate with weakly dependent data, making it challenging to obtain reliable inferences. To address this, we propose a blockwise bootstrap method that enables inference in such settings. Specifically, we consider a block length of L and a sample size of T. We have a total of $T - L + 1$ overlapping blocks, with the j-th block denoted as $\{(Y_{t+h}, Y_t, Z_t, D_t)\}_{t=j}^{j+L}$ for $j = 1, \cdots, T - L + 1$. Let N be the smallest natural number such that $N \cdot L \geq T$. To perform the blockwise bootstrap, we randomly select N blocks with replacement from the set of $T - L + 1$ available blocks and lay them end-to-end in the order sampled.[4] We denote the bootstrapped sample as $\{(Y_{t+h}^b, Y_t^b, Z_t^b, D_t^b)\}_{t=1}^T$, where $b = 1, \cdots, B$ and B represents the number of replications. First, we compute $\hat{\psi}^b$ based on the bootstrapped sample. Using this estimated parameter, we calculate the bootstrapped distribution function as follows:

$$\hat{F}_j^{h,b}(q, \hat{\psi}^b) = \sum_{t=1}^{T} \frac{\mathbf{1}\{D_t^b = d_j\} \cdot \mathbf{1}\{Y_{t+h}^b \leq q\}}{p^j(Z_t^b, \hat{\psi}^b)} \Bigg/ \sum_{t=1}^{T} \frac{\mathbf{1}\{D_t^b = d_j\}}{p^j(Z_t^b, \hat{\psi}^b)}.$$

Second, we compute the bootstrapped quantile functions as $\hat{Q}_j^{h,b}(\tau, \hat{\psi}^b) = \inf\{q : \hat{F}_j^{h,b}(q, \hat{\psi}^b) \geq \tau\}$ and obtain the bootstrapped QPE as $\hat{\Delta}_j^h(\tau, \hat{\psi}^b) = \hat{Q}_j^{h,b}(\tau, \hat{\psi}^b) - \hat{Q}_0^{h,b}(\tau, \hat{\psi}^b)$. By making additional assumptions, we can study the asymptotic behavior of the bootstrap estimators.

Assumption 10 *(Asymptotic properties of $\hat{\psi}^b$) Assume that $\sqrt{T}(\hat{\psi}^b - \psi_0) = T^{-1/2} \sum_{t=1}^{T} \ell(D_t^b, Z_t^b, \psi_0) + o_p(1)$.*

Assumption 11 *(Block size) Assume that $L = C \cdot T^\rho$ with $0 < \rho < (p-2)/(2p-2))$ where p is the same as in Assumption 4.*

Assumption 10 specifies the asymptotic properties of the bootstrapped policy regime estimator $\hat{\psi}^b$. This ensures desirable properties of the estimator in the asymptotic limit. Alternatively, Assumption 11, derived from Radulović (2002), imposes conditions on the block size used in the blockwise bootstrap. These conditions are necessary to ensure the validity of the blockwise bootstrap method and its compatibility with the underlying data structure.

[4] We must exclude the last $NL - T$ observations from the last sampled block to ensure that the bootstrap sample size remains equal to T.

Theorem 4 *Suppose that Assumptions 1–11 hold. Then, conditional on the sample path with probability approaching one,*

$$\sqrt{T}(\hat{F}_{\cdot}^{h,b}(\cdot,\hat{\psi}^b) - \hat{F}_{\cdot}^{h}(\cdot,\hat{\psi})) \Rightarrow \mathcal{F}(\cdot,\cdot),$$
$$\sqrt{T}(\hat{Q}_{\cdot}^{h,b}(\cdot,\hat{\psi}^b) - \hat{Q}_{\cdot}^{h}(\cdot,\hat{\psi})) \Rightarrow \mathcal{Q}(\cdot,\cdot),$$
$$\sqrt{T}(\hat{\Delta}_{\cdot}^{h,b}(\cdot,\hat{\psi}^b) - \hat{\Delta}_{\cdot}^{h}(\cdot,\hat{\psi})) \Rightarrow \mathcal{R}(\cdot,\cdot),$$

where $\mathcal{F}(\cdot,\cdot)$*,* $\mathcal{Q}(\cdot,\cdot)$*, and* $\mathcal{R}(\cdot,\cdot)$ *are given in Theorems 1–3.*

Theorem 4 establishes the validity of the proposed blockwise bootstrap, which has been shown by Radulović (2002), and enables the construction of valid pointwise confidence intervals for QPE. The validity result in Theorem 4 can also be extended to the estimation of monetary policy effects as demonstrated in Angrist, Jordà, and Kuersteiner (2018). It is worth noting that the results presented in Theorems 1 to 4 hold uniformly over the indexes. Consequently, similar to the approach taken by Donald and Hsu (2014), these results can be utilized for constructing tests for the stochastic dominance relations between the distributions of the potential outcomes, tests for the Lorenz dominance relations between the potential outcomes, and a confidence band for QPE over a continuum of quantile indexes. We provide a detailed description of the step-by-step implementation procedures for constructing both pointwise confidence intervals and confidence bands for QPE in the supplement appendix.

3 The Effectiveness of US Macroprudential Policy

3.1 Data and Policy Propensity Score Specification

This analysis incorporates data relating to US macroprudential policy. A macroprudential tool is viewed as an instrument that can influence credit growth by inducing acceleration or deceleration. The data sources include the works of Elliott, Feldberg, and Lehnert (2013) for the period 1948–1993, Shim et al. (2013) for the period 1990–2012, and the International Monetary Fund's Integrated Macroprudential Policy (iMaPP) database compiled by

Alam et al. (2019) for the period 2013–2019. Elliott, Feldberg, and Lehnert (2013) thoroughly examine diverse macroprudential tools, represented as an ordered policy variable with values extending beyond –1 and 1 given the actions of tools considered. In contrast, Shim et al. (2013) and the iMaPP database frame macroprudential policy within the scope of an ordered policy variable ranging from –1 to 1. Our classification of these tools follows this latter approach, as depicted in Table 1. To elaborate further, we set the monthly policy variable D_t to 1 (-1) if there is one tightening (easing) tool adopted in a month and to 0 if no tightening or easing tool is adopted during time t. For cases where multiple macroprudential tools are employed during period t, the monthly policy variable D_t is defined as 1 (or 0, or -1) if the number of tightening tools surpasses (equals, or is less than) the number of easing tools. In such cases, when the policy variable D_t is equal to 1 (or 0, or -1), it signifies a tightening (unchanging, or easing) macroprudential policy at time t.[5]

Figure 1 presents the monthly macroprudential actions from February 1948 to December 2019. Within this period, 50 months saw tightening actions implemented, whereas easing actions were adopted in 90 months, and the remaining months observed no policy adjustments. The shaded gray areas in Figure 1 denote recession periods as defined by the NBER. Notably, the frequency of easing actions exceeded that of tightening actions, with 26 months introducing easing measures and 5 months adopting tightening actions during recessions. After 1984, the US diminished its utilization of macroprudential policies. Only three easing macroprudential policies were launched between 1985 and 2007, specifically in 1986 (April), 1990 (December), and 1992 (April). As per the data from Shim et al. (2013), easing measures related to housing markets were enacted in the US in 2008 (July), 2009 (February), and 2009 (November), and a tightening measure was introduced in 2010 (September). Starting from 2014, as recorded by the iMaPP database, tightening measures were initiated every January until 2018, with an additional action in October 2018.

We focus on real bank credit growth responses to macroprudential actions in all commercial banks. Bank credit for all commercial banks has two major components: (1) securities

[5] Our definition of the policy variable D_t aligns with methodologies used in earlier works by Forbes, Fratzscher, and Straub (2015) and Richter, Schularick, and Shim (2019).

and (2) loans and leases. The outcome variable is defined as:

$$Y_{t+h} = \ln(y_{t+h}) - \ln(y_{t-1}),$$

where y is bank credit deflated by the consumer price index (CPI), and Y_{t+h} denotes the change in the log of real bank credit between the base month $t-1$ and month $t+h$ over varying prediction horizons $h = 0, 1, 2, \cdots, H$. We set $H = 24$ in this paper. By performing QPE at specific quantiles or the entire distribution of outcomes, we can assess the effects of policy at any point within its distribution.

We utilize an ordered probit model to determine the policy propensity score $(p^j(Z_t, \psi))$ for macroprudential actions, using a selection of covariates (Z_t). We select variables such as the inflation rate and industrial production growth rate based on macroeconomic theory, which states that these factors are integral to policy decisions and credit growth (Elliott, Feldberg, and Lehnert, 2013; Jordà, Schularick and Taylor, 2013). Acknowledging the potential impact of credit policy on financial market stabilization, we expand our propensity score model to include variables like the growth rate of the real house price index, the cyclically adjusted price–earnings (CAPE) ratio, the 3-month Treasury bill rate, and the yield curve spread. These additional variables are drawn from Elliott, Feldberg, and Lehnert (2013); Shiller (2016); and Jordà, Schularick, and Taylor (2013), and Monnet (2014). Our choice of conditioning variables reflects the unique characteristics of the US macroeconomic policy context and the specifics of our dataset. Considering the coordination between macroprudential and monetary policy in the US, we also include variables linked to monetary policy, like reserves and monetary base growth rates. This selection ensures we cover the primary factors influencing both policy decisions and bank credit growth, thereby safeguarding the validity of the unconfoundedness assumption in our study.[6]

[6] We extract data from reliable sources. Variables such as bank credit, the industrial production index, the consumer price index, reserve money, the 3-month Treasury bills interest rate, and the 10-year government bond yields are from FRED. S&P 500 stock prices, CAPE, and the real home price index are from Shiller (2016). All these variables, except interest variables and the yield curve spread, are taken from their official, seasonally adjusted values and converted into annual growth rates. To account for inflation, we transform bank credit, equity price index, and monetary aggregates into real values by dividing them by CPI.

Table 2 reports the average marginal effects of the policy predictors on the likelihood of a tightening action. We incorporate three lags for both the tightening and easing actions. The chosen lag length is determined using Akaike's Information Criterion (AIC). Other variables considered in estimating the policy propensity score are lagged for one period. In column (1) of Table 2, rises in the inflation rate, real bank credit, and the industrial production index increase the likelihood of tightening actions. This confirms the countercyclical purpose of macroprudential policy. However, only the growth rate of the industrial production index has a significant effect. In column (2) we further control variables relative to the equity market and interest rate. The result indicates that upsurges in both CAPE and the real home price index contribute to positive marginal effects on the probability of tightening actions, with CAPE exhibiting a notably more significant impact. Increasing the 3-month Treasury bill rate and yield curve spread also increases the likelihood of a tightening action, but only the yield curve spread coefficient is significant.

In columns (3) and (4) of Table 2, we examine the impact of including variables related to monetary policy. In column (4), the log-likelihood value indicates an improved fit when the monetary base variable is included. As a result, we consider the variables included in column (4) as the benchmark model for constructing the propensity score. However, when we compare the AIC values across all four propensity score models, we find that the model in column (2) has the smallest AIC value. This indicates that the model in column (2) performs better in terms of model fit and complexity. One explanation for this discrepancy is the high volatility of reserves and monetary bases, particularly during the most recent financial crisis. As a robustness check for our empirical results, we also consider the model that includes the variables from column (2). This additional analysis is presented in Section 3.3, where we assess the robustness of our findings.

Regarding the testability of the unconfoundedness assumption, we acknowledge that although it is considered untestable, Angrist and Kuersteiner (2011) and Angrist, Jordà, and Kuersteiner (2018) have proposed methods that allow for testing this assumption under certain conditions in time series settings. However, these methods require simultaneous testing for the martingale difference sequences property of a continuum of processes indexed in a function space, which is challenging in practice. In response to these difficulties, we have employed a sensitivity analysis, as detailed in the supplementary appendix under the section titled "Sensitivity Analysis of the Unconfoundedness Assumption," considering potential omitted variables. This analysis illuminates the robustness of our findings and helps address concerns about the operational complexities and stringent prerequisites of these tests, which demand high computational resources and are thus less feasible in our empirical study. Sensitivity analysis serves as a more practical tool in this context because it evaluates the impact of unmeasured confounding variables without enforcing strict assumptions, thereby generating plausible estimates across various confounding scenarios. This approach enhances the reliability and robustness of our results, proving effective in managing the challenges of unconfoundedness.

3.2 Benchmark Empirical Results

The main goal of macroprudential policy, as discussed earlier, is to regulate fluctuations in the financial market. The macroprudential authorities implement tightening actions to control excessive credit growth whereas easing actions aim to stimulate conditions when credit is low. Our analysis employs QPE and US data to evaluate the impacts of these macroprudential policies, providing an advantageous look into effects across the distribution of real bank credit growth. For the computation of confidence intervals for the empirical distribution of QPE, we use the blockwise bootstrap method, repeating the procedure 2,000 times. The sensitivity of results to block length selection is acknowledged, leading us to choose an optimal length in line with the Hall, Horowitz, and Jing (1995) and Horowitz (2019) methodology, where $L = C \cdot T^{\rho}$ with $\rho = 1/5$ and $C = 1$. Table 3 presents the estimated effects of both tightening and easing actions across various quantiles (0.1-th, 0.3-th, 0.5-th, 0.7-th, 0.9-th) of real bank credit growth. The table's upper panel displays tightening action results, whereas the lower panel covers easing actions. For comparative purposes, we also present the average policy effect estimation results by Angrist, Jordà, and Kuersteiner (2018), thereby assessing the impact of macroprudential policies. All estimates are presented with bootstrapped 95% confidence intervals indicated in square brackets.

The average policy effect results from Table 3 reveal that macroprudential policies significantly negatively impact real bank credit growth for tightening actions. These effects persist for 3 to 9 months after implementing macroprudential actions, indicating their potential effectiveness in controlling average credit growth. However, whereas the average responses suggest effectiveness, it does not necessarily imply overall effectiveness in terms of credit growth. Further analysis of bank credit growth responses at different quantiles reveals heterogeneity in the results. Specifically, the QPE estimates are significantly negative only for the 0.1-th quantile at months 3, 6, and 9. For other quantiles and periods beyond 12 months, most QPE estimates are statistically insignificant. These results suggest that the effectiveness of tightening actions in reducing the risk of high bank credit growth diminishes after 12 months. In addition, the QPE estimates demonstrate an increasing trend along the quantiles. For instance, three months post-tightening actions, QPE estimates range from –1.924 (0.1-th quantile) to 0.009 (0.9-th quantile). A year later, they range from –3.047 to 0.386, indicating an increase in the estimated effects along with quantiles. Furthermore, the QPE estimates at the 0.9-th quantile become positive after a year of actions, representing tightening actions increase bank credit when credit growth is exceptionally high.

In the lower panel of Table 3, the average effects of easing actions on bank credit growth are insignificant. However, upon examining the QPE responses of easing actions at different quantiles, we find heterogeneity in the results, with the effects transitioning from negative to positive as we move along the quantiles. Specifically, the QPE estimates are positive at the middle and high quantiles of bank credit growth, but most of these estimates are statistically insignificant. In contrast, the effects are negative at the lower tail of credit growth, where easing actions are expected to have a significant impact. For instance, at the 0.1-th quantile, all QPE estimates are negative. These estimates become statistically significant 18 months after implementing the easing actions, indicating that adopting easing policies adversely affects bank credit growth when it is notably low. These findings highlight the dependence of policy effectiveness on the quantiles of credit growth. It is crucial to consider more than just the average impact of policies to determine their effectiveness in reducing the risk of excessive credit growth.

As discussed, macroprudential policy aims to minimize fluctuations in the financial market. Tightening actions are then implemented by the authorities to address excessive credit growth whereas easing actions aim to stimulate low credit conditions. We present the QPE results for these actions across various bank credit growth quantiles in Table 4. From the upper panel of Table 4, we observe that the QPE estimates for tightening actions are initially negative at high quantiles for up to 9 months after implementation. However, after one year, the QPE estimates turn positive for quantiles higher than 0.80. Notably, at the 0.95-th quantile of bank credit growth, the responses to tightening actions are significantly positive, with a QPE estimate of 4.436 observed two years after the actions. These results suggest that adopting tightening actions further increases high credit growth and introduces additional risks to the financial market one year after implementing the policy. Turning to the lower panel of Table 4, we find that nearly all QPE estimates for easing actions at low quantiles of bank credit growth are negative across all time horizons, which indicates that easing actions have adverse effects on low quantiles of credit growth. For instance, at the 0.05-th quantile of credit growth, the QPE estimate is significantly negative, with estimates of –2.309 two years after implementing the actions. These results imply that a stimulation policy has an immediate reverse effect when the financial market experiences extremely low credit growth. Overall, our findings highlight the adverse impact of easing actions on the financial markets, particularly regarding stimulating effects on credit growth. These findings underscore the importance of considering the impacts at different quantiles in understanding the efficacy of macroprudential policies.

To illustrate the asymmetric effects of macroprudential policy on credit growth, which depend on the quantiles of credit growth, we present the impulse response functions based on both average policy effects and QPE in Figures 2 and 3. In the upper panel of Figure 2, we observe that the average policy effects of tightening actions are negative and effective up to 12 months after implementation. However, the three lower panels of Figure 2, representing the 0.85-th, 0.90-th, and 0.95-th quantiles, reveal a different pattern. Initially, the effects are around zero and gradually turn positive approximately nine months after implementation. Furthermore, these effects continue to increase over time. These results suggest tightening actions may inadvertently expand credit when bank credit growth is exceptionally high. Conversely, Figure 3 demonstrates that whereas the average policy effects are positive 3 to 6 months after implementing easing actions, they transition to negative over time and consistently deepen. The QPE at lower quantiles remain negative across the entire horizon, implying that easing actions could reduce bank credit when credit growth is low. These findings underscore the importance of considering both average and quantile effects to understand better the differential impact of macroprudential policy under diverse financial conditions.

3.3 Robustness Checks

In this section, we conduct robust checks to ensure the reliability of our proposed method. We begin by examining the impact on two elements of bank credit: securities and bank loans and leases. Our analysis at specific intervals, spanning 0, 6, 12, 18, and 24 months, is in Tables 5 and 6. The top sections of Tables 5 and 6 show that tightening actions reduce low quantiles of real securities and loans and leases but increase high quantiles. Furthermore, the lower sections of both tables indicate that the QPE estimates of easing actions for low quantiles of real securities are negative, with positive estimates for high quantiles. The results suggest that tightening actions may not limit high securities growth whereas easing policies struggle to stimulate financial markets when securities growth is low. The findings presented in Tables 5 and 6 align closely with those in Tables 3, further emphasizing the robustness of our methodology in evaluating US macroprudential policy. However, it is worth noting that the average policy effect estimates of tightening actions for real securities are all negative, whereas they are all positive for real loans and leases. The results suggest that the results of tightening actions based on the average policy effects method are less robust.

Next, although most previous studies use real bank credit as the outcome variable of interest, nominal bank credit growth usually varies during high inflation periods, confounding the policy effect. To demonstrate the robustness of the empirical results, we alter our focus to the change in nominal bank credit growth as in Cizel et al. (2019). Table 7 presents the estimated effects of macroprudential policy on credit growth. Interestingly, tightening actions initially negatively impact average nominal credit growth, but after one year, it becomes positive. Conversely, easing actions have an immediate positive average policy effect that turns negative after one year. Analyzing the QPE estimates, we find that tightening actions mostly yield negative effects for low quantiles but positive effects for the 0.9-th quantile. The responses of easing actions on nominal credit growth mirror those observed for real credit growth. Notably, based on the empirical results from Table 7, it is evident that easing actions struggle to stimulate low nominal bank credit growth in the financial market. Our findings, presented in Tables 5 to 7, reinforce the suitability of the proposed QPE methodology for evaluating macroprudential policy effects.

We expand our analysis by incorporating additional lags of the covariates within the propensity score model. The benchmark model is limited to considering only a single lag of related macroeconomic variables. This restriction may not sufficiently encapsulate the full spectrum of information that policymakers potentially evaluate when deciding upon policy measures. To test the robustness, we incorporate two to three lags of the covariates within our propensity-score models. The contrast between impulse response functions under various lag conditions is demonstrated in Figure 4. The solid black lines in this figure depict the estimated QPE of the benchmark model. The gray dashed lines represent the estimated QPE when two lags are included in the propensity score model. The gray dotted lines chart the estimated QPE when three lags are incorporated. The QPE estimates resulting from policy easing actions across all three quartiles and those resulting from tightening actions at the third quartile exhibit a close correlation and similar trend. The remaining estimates do not present any significant divergence from the baseline model. When three lags are introduced, we note minor adjustments in the QPE estimates for tightening actions at the first and second quartiles. However, these shifts remain marginal. In conclusion, our analysis confirms the robustness of the QPE when integrating additional covariate lags into the propensity score model.

Furthermore, we enhance the stability and credibility of our results using a specific propensity score model (see column (2) in Table 2) chosen for robustness. This model exhibits the lowest AIC value, striking a favorable balance between complexity and fit. This model differs from our primary model in one key respect: it does not include the variables related to the monetary base and reserves. Although these factors are important for both the outcome and policy variables, they were highly volatile during the 2007–2009 financial crisis, which may make them less suitable for our model. Table 8 provides the results of this model. Despite excluding certain variables in the propensity score model, the observed effects of both easing and tightening actions on bank credit growth remain the same. This suggests that our benchmark findings are not heavily dependent on these excluded variables, reinforcing their validity.

While in most months, only a single policy was implemented, there were instances where the authority simultaneously executed multiple macroprudential actions. For our benchmark empirical study, we aggregated multiple macroprudential actions into a scale of –1, 0, 1. Condensing multiple actions into a –1 to 1 scale may result in some loss of information, and the QPE estimates may encompass the impacts of multiple policies. To address this concern, we follow the approach used by Angrist, Jordà, and Kuersteiner (2018) by allowing the policy variable to adopt five categories, represented as $-2, -1, 0, 1, 2$. The ± 2 categories reflect the enactment of more than two policies, either tightening or easing. We compute the policy propensity score using an ordered probit model considering all five changes and report causal effects for the most prevalent categories of the ± 1 changes. Table 9 shows that a tightening macroprudential policy leads to decreased bank credit on average and low quantiles but increased bank credit in high quantiles. Conversely, an easing macroprudential policy increases bank credit on average and high quantiles but decreases bank credit in low quantiles. These results, obtained using five categories, are like the benchmark results obtained with three categories.

Finally, given the limited macroprudential actions observed from 1983 until the financial crisis, our analysis focuses on a subsample from 1948 to 1983. Figure 1 supports this choice, which depicts a decline in the utilization of macroprudential actions during the later period. By concentrating on the earlier period, we can assess the effectiveness of macroprudential policy without the potential distortion caused by the reduced frequency of actions. Table 10 presents the estimated effects, and despite excluding the 1984–2017 sample, the difference between the longer extended period (1948–2017) and the early period (1948–1983) is not substantial. This approach provides insights into the effects of macroprudential policy during a more active period, further bolstering the reliability of our analysis.

4 Conclusion and Discussion

In this paper, we propose a novel application of QPE to assess the impact of macroprudential policies on bank credit growth. Building upon the theoretical groundwork laid by Angrist, Jordà, and Kuersteiner (2018), we extend their analysis of the average policy effect to QPE and adapt the cross-sectional frameworks developed by Firpo (2007), Cattaneo (2010), and Donald and Hsu (2014) to a time series context. Our empirical investigation of US macroprudential policy shows that tightening such policies does not effectively suppress high credit growth. Conversely, easing policies during periods of low credit growth do not stimulate bank credit growth significantly. Consequently, our findings challenge the efficacy of these macroprudential policies in mitigating high-risk bank credit growth and achieving financial stability in the US context.

However, we must acknowledge the limitations inherent to our study. Our reliance on aggregate time series data inhibits our ability to examine the diverse responses of individual banks to macroprudential policies. Although our findings suggest a limited influence of these policies on bank credit growth at higher quantiles, it does not unequivocally establish the ineffectiveness of such policies. Indeed, these policies might offer additional advantages or manifest varied effects at the individual bank level, aspects beyond the purview of our current study. Given the intricate nature of these dynamics, future research focused on quantile causal effects using bank-specific panel data could shed more light on the nuances of macroprudential policy impact. Developing this approach is a promising avenue for deeper insights in the field.

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Table 1: Types of Macroprudential Tools

Policy instrument	Tightening tools	Easing tools
Tools affecting demand for credit		
Underwriting standards	Lowering loan maturity limits, loan-to-value limits or debt-to-income ratio limits	Increasing loan maturity limits, loan-to-value limits or debt-to-income ratio limits
Margin requirements	Setting minimum investment levels to limit the investor's leverage	
Tax-related policies		Increasing the amount of tax credit for homebuyers
Tools affecting supply of credit		
Interest rate ceilings	Lowering the deposit rate ceilings	Raising the deposit rate ceilings
Reserve requirements	Raising reserve requirements	Lowering reserve requirements
Liquidity requirements	Raising minimum requirements for liquidity coverage ratios	Lowering minimum requirements for liquidity coverage ratios
Capital requirements	Tightening capital standards	Easing capital standards
Portfolio restrictions	Tightened the restrictions on the types of loans banks could hold in a portfolio	Eased the restrictions on the types of loans banks could hold in a portfolio
SIFI	Tightening capital standards of globally and domestically significant financial institutions (SIFIs)	
Supervisory pressure	Discouraging excessive credit growth	Promoting credit availability

Source: Elliott, Feldberg, and Lehnert (2013), Shim et al. (2013), and Alam et al. (2019).

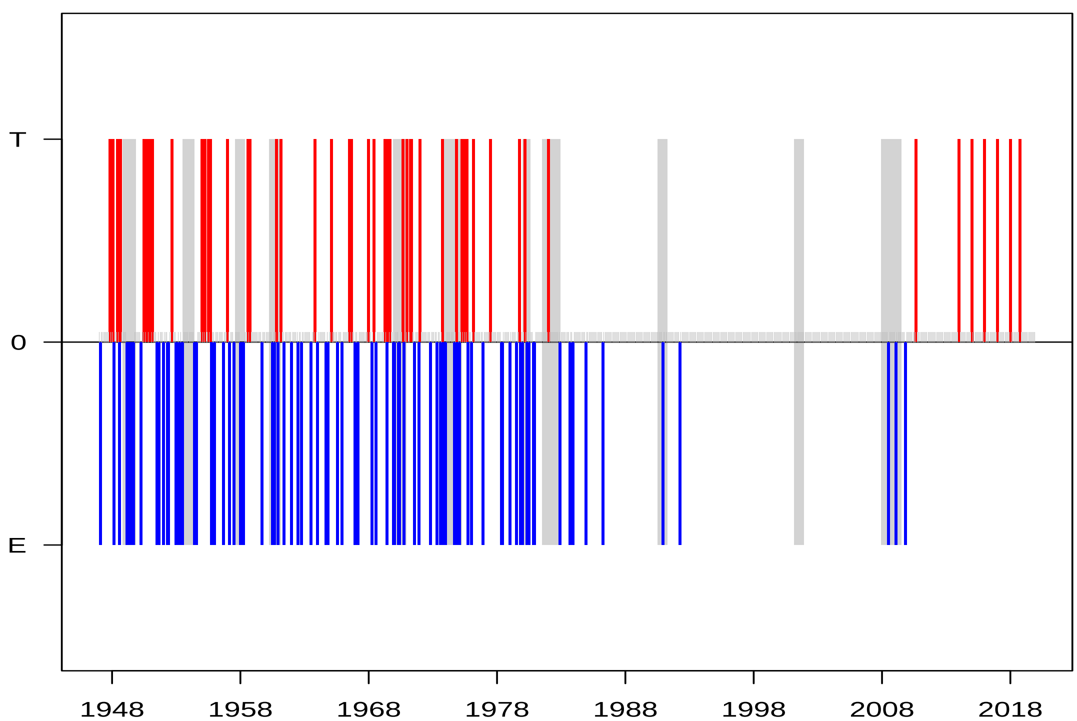


Figure 1: Macroprudential Actions in the US

Table 2: Ordered Probit Specification for Macroprudential Policy

Variable	(1)	(2)	(3)	(4)
Easing actions $_{t-1}$	-2.091**	-1.013	-1.011	-1.027
	(0.992)	(0.984)	(0.986)	(0.985)
Easing actions $_{t-2}$	-0.870	0.100	0.101	0.086
	(1.004)	(0.993)	(0.994)	(0.994)
Easing actions $_{t-3}$	0.853	1.804*	1.805*	1.791*
	(0.988)	(0.980)	(0.981)	(0.980)
Tightening actions $_{t-1}$	-1.064	-0.599	-0.599	-0.598
	(1.188)	(1.145)	(1.145)	(1.144)
Tightening actions $_{t-2}$	2.866**	3.385***	3.384***	3.384***
	(1.187)	(1.185)	(1.185)	(1.184)
Tightening actions $_{t-3}$	0.461	0.854	0.853	0.851
	(1.039)	(1.000)	(1.000)	(1.000)
Growth of real bank credit $_{t-1}$	0.276	0.373**	0.372**	0.374**
	(0.168)	(0.177)	(0.179)	(0.177)
Growth of industrial production $_{t-1}$	0.274**	0.307***	0.308***	0.302***
	(0.115)	(0.115)	(0.116)	(0.116)
Ind. pro. growth × credit growth $_{t-1}$	-0.044**	-0.040**	-0.040**	-0.040**
	(0.021)	(0.020)	(0.020)	(0.020)
CPI inflation $_{t-1}$	0.130	0.732**	0.733**	0.729**
	(0.196)	(0.286)	(0.288)	(0.286)
Growth of real home price index $_{t-1}$		0.024	0.025	0.015
		(0.12)	(0.127)	(0.124)
CAPE ratio $_{t-1}$		0.303***	0.303***	0.303***
		(0.087)	(0.087)	(0.087)
3-month treasury bill rate $_{t-1}$		-0.046	-0.046	-0.044
		(0.252)	(0.252)	(0.252)
Yield curve spread $_{t-1}$		2.073***	2.072***	2.104***
		(0.555)	(0.557)	(0.568)
Growth rate of reserves $_{t-1}$			0.000	
			(0.006)	
Growth rate of monetary base $_{t-1}$				-0.012
				(0.044)
Log Likelihood	-450.35	-436.99	-436.99	-436.95
AIC	924.69	905.98	907.98	907.91

Notes: This table reports marginal effects on the probability of tightening actions. The reported coefficients are multiplied by 100. Standard errors are shown in parentheses. ***,**, and * denote significance at 99%, 95%, 90% levels, respectively.

	APE	$\tau = 0.1$	$\tau = 0.3$	$\tau = 0.5$	$\tau = 0.7$	$\tau = 0.9$
	Tightening Actions					
0	-0.245*	-0.226	-0.260	-0.211	-0.104	-0.278
	[-0.413, -0.076]	[-0.660, 0.208]	[-0.595, 0.074]	[-0.572, 0.150]	[-0.425, 0.218]	[-0.546, -0.011]
3	-0.813*	-1.924*	-1.386	-0.454	-0.051	0.009
	[-1.471, -0.154]	[-3.478, -0.369]	[-3.311, 0.538]	[-1.726, 0.818]	[-0.919, 0.817]	[-0.681, 0.699]
6	-1.177*	-2.268*	-1.842	-0.639	-0.142	-0.373
	[-2.130, -0.223]	[-4.275, -0.261]	[-4.270, 0.586]	[-2.723, 1.445]	[-1.409, 1.124]	[-1.300, 0.553]
9	-1.415*	-2.917*	-2.194	-0.718	-0.642	-0.441
	[-2.679, -0.151]	[-5.678, -0.157]	[-5.516, 1.129]	[-3.135, 1.698]	[-2.265, 0.980]	[-1.882, 1.001]
12	-1.190	-3.047	-1.903	-0.736	-0.070	0.368
	[-2.889, 0.510]	[-6.436, 0.342]	[-5.478, 1.671]	[-3.801, 2.329]	[-2.438, 2.299]	[-1.517, 2.253]
15	-1.110	-1.950	-2.703	-1.837	0.397	1.697
	[-3.207, 0.986]	[-5.004, 1.103]	[-7.181, 1.774]	[-5.687, 2.013]	[-2.711, 3.506]	[-1.017, 4.411]
18	-1.096	-1.902	-1.977	-2.986	-0.237	2.600
	[-3.594, 1.403]	[-6.018, 2.213]	[-5.345, 1.390]	[-8.106, 2.135]	[-4.179, 3.704]	[-1.278, 6.477]
21	-1.177	-1.957	-3.007	-3.336	-0.943	2.087
	[-4.047, 1.693]	[-6.272, 2.358]	[-6.729, 0.714]	[-8.415, 1.742]	[-5.207, 3.321]	[-1.059, 5.233]
24	-0.987	-1.017	-3.051	-2.551	-1.004	1.472
	[-4.280, 2.305]	[-6.648, 4.614]	[-7.059, 0.956]	[-6.914, 1.812]	[-5.934, 3.926]	[-2.764, 5.707]
	Easing Actions					
0	0.051	-0.380	-0.010	0.118	0.173	0.337*
	[-0.106, 0.208]	[-0.872, 0.112]	[-0.251, 0.231]	[-0.104, 0.341]	[-0.071, 0.417]	[0.129, 0.545]
3	0.104	-0.556	-0.246	0.049	0.671	1.081*
	[-0.323, 0.531]	[-1.653, 0.541]	[-0.997, 0.505]	[-0.639, 0.736]	[-0.063, 1.405]	[0.195, 1.967]
6	0.036	-0.364	-0.078	0.388	0.979*	0.745*
	[-0.520, 0.593]	[-1.642, 0.915]	[-1.286, 1.130]	[-0.827, 1.602]	[0.262, 1.696]	[0.054, 1.436]
9	-0.406	-0.970	-0.715	-0.025	0.677	0.529
	[-1.188, 0.375]	[-3.270, 1.330]	[-2.036, 0.606]	[-1.733, 1.683]	[-0.038, 1.393]	[-0.331, 1.389]
12	-0.534	-1.832	-0.879	0.358	0.533	0.102
	[-1.491, 0.423]	[-3.883, 0.220]	[-2.586, 0.827]	[-1.432, 2.149]	[-0.441, 1.507]	[-1.240, 1.445]
15	-0.704	-1.571	-1.252	0.427	0.567	0.393
	[-1.840, 0.432]	[-3.347, 0.204]	[-3.344, 0.840]	[-1.989, 2.843]	[-0.487, 1.621]	[-1.483, 2.270]
18	-0.928	-2.522*	-2.388	0.680	0.257	0.704
	[-2.263, 0.408]	[-4.816, -0.229]	[-5.273, 0.497]	[-2.417, 3.776]	[-1.366, 1.88]	[-0.855, 2.263]
21	-1.228	-3.173*	-2.809	-0.119	0.555	0.514
	[-2.732, 0.276]	[-6.098, -0.247]	[-6.425, 0.808]	[-2.782, 2.544]	[-1.192, 2.302]	[-0.686, 1.715]
24	-1.511	-3.994*	-3.394	0.312	0.407	0.961
	[-3.133, 0.112]	[-7.135, -0.853]	[-7.484, 0.697]	[-2.903, 3.526]	[-1.996, 2.811]	[-0.897, 2.820]

Notes: APE denotes the average policy effects. The first column is months after the actions. * denotes significance at the 95% level. [,] are the 95% bootstrap confidence intervals for the estimator of QPE.

Table 3: Estimates of Responses of Real Bank Credit to Macroprudential Actions

	Tightening Actions				
	$\tau = 0.75$	$\tau = 0.80$	$\tau = 0.85$	$\tau = 0.90$	$\tau = 0.95$
0	-0.149	-0.197	-0.190	-0.278*	-0.331
	[-0.366, 0.069]	[-0.398, 0.005]	[-0.428, 0.048]	[-0.546, -0.011]	[-0.930, 0.267]
3	-0.110	-0.007	0.077	0.009	-0.236
	[-1.000, 0.780]	[-0.759, 0.745]	[-0.638, 0.791]	[-0.681, 0.699]	[-0.914, 0.442]
6	-0.234	-0.269	-0.368	-0.373	-0.225
	[-1.298, 0.829]	[-1.445, 0.907]	[-1.525, 0.789]	[-1.300, 0.553]	[-1.461, 1.011]
9	-0.376	0.201	-0.058	-0.441	-0.366
	[-1.638, 0.886]	[-1.470, 1.871]	[-1.519, 1.403]	[-1.882, 1.001]	[-1.676, 0.943]
12	0.017	0.723	0.887	0.368	0.460
	[-2.292, 2.326]	[-1.690, 3.136]	[-1.441, 3.214]	[-1.517, 2.253]	[-1.710, 2.630]
15	-0.082	0.854	0.856	1.697	1.098
	[-3.125, 2.961]	[-2.762, 4.470]	[-1.236, 2.947]	[-1.017, 4.411]	[-0.862, 3.058]
18	-0.741	0.318	0.958	2.600	2.235
	[-5.104, 3.622]	[-3.285, 3.921]	[-1.961, 3.877]	[-1.278, 6.477]	[-1.005, 5.475]
21	-1.443	1.119	1.134	2.087	2.963
	[-6.048, 3.161]	[-2.851, 5.090]	[-2.969, 5.236]	[-1.059, 5.233]	[-0.276, 6.202]
24	-0.785	1.011	1.704	1.472	4.436*
	[-5.141, 3.571]	[-3.862, 5.883]	[-2.899, 6.307]	[-2.764, 5.707]	[0.346, 8.526]
	Easing Actions				
	$\tau = 0.05$	$\tau = 0.10$	$\tau = 0.15$	$\tau = 0.20$	$\tau = 0.25$
0	-0.262	-0.380	-0.201	-0.106	-0.010
	[-0.596, 0.072]	[-0.872, 0.112]	[-0.597, 0.195]	[-0.564, 0.352]	[-0.326, 0.306]
3	-0.751	-0.556	-0.090	-0.241	-0.360
	[-1.728, 0.225]	[-1.653, 0.541]	[-1.317, 1.137]	[-1.030, 0.548]	[-1.235, 0.515]
6	0.015	-0.364	-0.812	-0.393	-0.312
	[-1.962, 1.992]	[-1.642, 0.915]	[-1.946, 0.322]	[-1.583, 0.797]	[-1.453, 0.829]
9	-1.782	-0.97	-0.541	-0.772	-0.763
	[-4.016, 0.452]	[-3.270, 1.330]	[-2.804, 1.721]	[-2.166, 0.622]	[-1.928, 0.403]
12	-0.818	-1.832	-1.581	-0.769	-1.174
	[-2.699, 1.063]	[-3.883, 0.220]	[-3.638, 0.477]	[-2.809, 1.270]	[-3.054, 0.705]
15	-0.899	-1.571	-2.115	-1.898	-1.225
	[-2.670, 0.872]	[-3.347, 0.204]	[-4.453, 0.222]	[-4.012, 0.216]	[-3.513, 1.063]
18	-1.059	-2.522*	-2.113	-2.292*	-2.277*
	[-2.680, 0.561]	[-4.816, -0.229]	[-4.295, 0.070]	[-4.261, -0.323]	[-4.016, -0.539]
21	-1.307	-3.173*	-2.543*	-2.531*	-2.684*
	[-3.133, 0.519]	[-6.098, -0.247]	[-4.944, -0.141]	[-4.826, -0.237]	[-5.194, -0.174]
24	-2.309*	-3.994*	-2.683	-1.882	-2.799
	[-4.358, -0.259]	[-7.135, -0.853]	[-5.634, 0.268]	[-4.962, 1.199]	[-5.711, 0.114]

Notes: The first column is months after the actions. * denotes significance at the 95% level. [,] are the 95% bootstrap confidence intervals for the estimator of QPE.

Table 4: Tail Responses of Real Bank Credit to Macroprudential Actions

	Tightening Actions					
	APE	$\tau = 0.1$	$\tau = 0.3$	$\tau = 0.5$	$\tau = 0.7$	$\tau = 0.9$
0	-0.356	-0.543*	-0.470	-0.287	-0.373	0.071
	[-0.781, 0.068]	[-1.035, -0.050]	[-1.090, 0.150]	[-0.891, 0.317]	[-1.452, 0.706]	[-0.722, 0.865]
6	-1.695	-5.111	-2.963	-1.624	-0.266	-0.899
	[-3.661, 0.271]	[-10.435, 0.212]	[-6.523, 0.596]	[-4.967, 1.719]	[-2.998, 2.466]	[-7.262, 5.463]
12	-2.017	-7.071*	-4.787	-0.739	0.736	-0.209
	[-4.828, 0.793]	[-14.022, -0.121]	[-11.412, 1.838]	[-5.578, 4.101]	[-3.280, 4.751]	[-4.223, 3.805]
18	-2.426	-6.430	-4.496	-3.621	0.199	0.211
	[-6.001, 1.148]	[-14.684, 1.824]	[-10.917, 1.925]	[-11.496, 4.254]	[-5.151, 5.548]	[-5.565, 5.988]
24	-3.011	-9.011	-3.498	-2.979	0.971	-1.284
	[-6.889, 0.868]	[-20.636, 2.614]	[-12.557, 5.560]	[-10.352, 4.395]	[-4.765, 6.707]	[-5.992, 3.424]
	Easing Actions					
	APE	$\tau = 0.1$	$\tau = 0.3$	$\tau = 0.5$	$\tau = 0.7$	$\tau = 0.9$
0	0.125	-0.534	-0.040	0.171	0.148	0.548*
	[-0.174, 0.424]	[-1.195, 0.128]	[-0.452, 0.371]	[-0.233, 0.574]	[-0.696, 0.992]	[0.211, 0.884]
6	0.155	-1.525	-0.395	0.686	0.962	1.653
	[-0.865, 1.174]	[-3.725, 0.674]	[-2.315, 1.525]	[-1.024, 2.397]	[-0.270, 2.195]	[-0.300, 3.605]
12	-0.718	-2.187	-2.139	-0.767	-0.026	0.658
	[-2.223, 0.787]	[-4.481, 0.106]	[-5.553, 1.274]	[-3.780, 2.245]	[-3.087, 3.036]	[-1.541, 2.858]
18	-1.360	-3.042	-1.820	-1.847	0.290	-0.828
	[-3.225, 0.505]	[-8.531, 2.446]	[-4.185, 0.545]	[-4.432, 0.739]	[-4.386, 4.967]	[-4.825, 3.168]
24	-2.511*	-3.978	-2.491	-2.677*	-1.825	-0.406
	[-4.492, -0.531]	[-8.343, 0.386]	[-5.898, 0.917]	[-5.042, -0.311]	[-5.418, 1.767]	[-4.404, 3.592]

Notes: APE denotes the average policy effects. The first column is months after the actions. * denotes significance at the 95% level. [,] are the 95% bootstrap confidence intervals for the estimator of QPE.

Table 5: QPE Estimates of Real Securities to Macroprudential Actions

			Tightening Actions			
	APE	$\tau = 0.1$	$\tau = 0.3$	$\tau = 0.5$	$\tau = 0.7$	$\tau = 0.9$
0	0.003	-0.330	-0.184	0.141	0.188	0.123
	[-0.309, 0.314]	[-0.947, 0.286]	[-0.751, 0.383]	[-0.392, 0.673]	[-0.149, 0.525]	[-0.269, 0.515]
6	0.245	-3.449	0.107	0.724	0.855	1.855
	[-1.854, 2.343]	[-9.261, 2.363]	[-3.269, 3.483]	[-1.320, 2.767]	[-0.881, 2.591]	[-0.947, 4.658]
12	0.732	-3.388	0.704	1.060	2.505	2.905
	[-2.929, 4.393]	[-10.786, 4.010]	[-4.724, 6.131]	[-1.872, 3.991]	[-0.943, 5.952]	[-1.113, 6.923]
18	1.182	-2.298	0.195	2.138	3.529	4.301
	[-3.907, 6.270]	[-10.996, 6.401]	[-6.348, 6.739]	[-2.420, 6.697]	[-0.720, 7.778]	[-1.082, 9.684]
24	1.802	-0.881	0.169	4.015	3.742	3.192
	[-4.679, 8.282]	[-10.275, 8.513]	[-7.485, 7.824]	[-4.275, 12.305]	[-0.594, 8.077]	[-1.817, 8.201]
			Easing Actions			
	APE	$\tau = 0.1$	$\tau = 0.3$	$\tau = 0.5$	$\tau = 0.7$	$\tau = 0.9$
0	0.016	-0.106	0.094	0.056	0.155	0.134
	[-0.144, 0.177]	[-0.585, 0.372]	[-0.152 , 0.340]	[-0.095, 0.206]	[-0.077, 0.387]	[-0.114, 0.382]
6	-0.033	-0.202	0.424	0.156	0.551	0.815
	[-0.815, 0.749]	[-2.074, 1.671]	[-1.451, 2.300]	[-0.946, 1.257]	[-0.286, 1.388]	[-0.504, 2.133]
12	-0.318	-1.173	-0.356	1.041	1.051	0.887
	[-1.626, 0.990]	[-4.250, 1.905]	[-2.947, 2.235]	[-0.560, 2.641]	[-0.726, 2.828]	[-0.548, 2.321]
18	-0.543	-0.894	-0.515	1.505*	1.432	2.046
	[-2.340, 1.254]	[-3.992, 2.203]	[-5.559, 4.528]	[-2.292, 5.302]	[-0.373, 3.237]	[-0.167, 4.258]
24	-0.399	-3.192	-1.468	1.556	2.268	2.490
	[-2.705, 1.907]	[-8.212, 1.828]	[-7.019, 4.083]	[-1.224, 4.335]	[-0.062, 4.598]	[-0.276, 5.256]

Notes: APE denotes the average policy effects. The first column is months after the actions. * denotes significance at the 95% level. [,] are the 95% bootstrap confidence intervals for the estimator of QPE.

Table 6: QPE Estimates of Real Loans and Leases to Macroprudential Actions

			Tightening Actions			
	APE	$\tau = 0.1$	$\tau = 0.3$	$\tau = 0.5$	$\tau = 0.7$	$\tau = 0.9$
0	-0.128	-0.223	0.006	-0.020	-0.100	-0.208*
	[-0.393, 0.137]	[-0.810, 0.363]	[-0.378, 0.390]	[-0.190, 0.149]	[-0.294, 0.094]	[-0.408, -0.009]
6	-0.581	2.174	-1.084	-0.132	-0.773	0.322
	[-2.333, 1.171]	[-4.537, 0.188]	[-3.213, 1.045]	[-1.657, 1.394]	[-2.632, 1.085]	[-1.727, 2.371]
12	-0.376	-0.696	-1.601	-0.556	-0.027	1.033
	[-3.838, 3.086]	[-3.139, 1.747]	[-4.754, 1.553]	[-2.926, 1.815]	[-2.089, 2.034]	[-1.757, 3.823]
18	0.062	-1.023	-0.334	0.328	-0.646	2.553
	[-5.323, 5.448]	[-4.167, 2.121]	[-4.061, 3.393]	[-2.922, 3.578]	[-2.403, 1.111]	[-2.712, 7.818]
24	0.591	-1.743	-0.321	0.260	-0.214	5.161
	[-6.680, 7.863]	[-5.984, 2.499]	[-4.528, 3.885]	[-2.709, 3.229]	[-3.192, 2.763]	[-2.179, 12.500]
			Easing Actions			
	APE	$\tau = 0.1$	$\tau = 0.3$	$\tau = 0.5$	$\tau = 0.7$	$\tau = 0.9$
0	0.075	-0.129	-0.014	0.151	0.253	0.370*
	[-0.082, 0.233]	[-0.501, 0.243]	[-0.234, 0.207]	[-0.063, 0.365]	[0.039, 0.466]	[0.125, 0.615]
6	0.122	0.266	0.047	1.173*	1.050*	1.008*
	[-0.601, 0.844]	[-1.941, 2.474]	[-1.911, 2.005]	[0.554, 1.793]	[0.510, 1.589]	[0.053, 1.963]
12	-0.195	-0.164	0.866	1.022*	1.105	1.344
	[-1.413, 1.023]	[-1.013, 0.685]	[-1.527, 3.258]	[0.119, 1.925]	[-0.009, 2.219]	[-0.231, 2.918]
18	-0.384	0.124	1.173	1.237*	0.676	2.018
	[-2.060, 1.292]	[-2.302, 2.549]	[-1.118, 3.463]	[0.045, 2.429]	[-0.401, 1.754]	[-1.338, 5.375]
24	-0.760	-0.155	0.254	0.865	0.750	1.579
	[-2.926, 1.406]	[-2.428, 2.117]	[-2.774, 3.283]	[-1.198, 2.928]	[-1.054, 2.554]	[-2.022, 5.180]

Notes: APE denotes the average policy effects. The first column is months after the actions. * denotes significance at the 95% level. [,] are the 95% bootstrap confidence intervals for the estimator of QPE.

Table 7: QPE Estimates of Nominal Bank Credit to Macroprudential Actions

	APE	$\tau = 0.1$	$\tau = 0.3$	$\tau = 0.5$	$\tau = 0.7$	$\tau = 0.9$
				Tightening Actions		
0	-0.243*	-0.226	-0.260	-0.211	-0.104	-0.278*
	[-0.411, -0.076]	[-0.656, 0.204]	[-0.591, 0.071]	[-0.574, 0.152]	[-0.424, 0.217]	[-0.544, -0.012]
3	-0.802*	-1.924*	-1.386	-0.454	0.097	0.009
	[-1.451, -0.153]	[-3.447, -0.400]	[-3.195, 0.422]	[-1.724, 0.816]	[-0.665, 0.860]	[-0.662, 0.680]
6	-1.162*	-2.378*	-1.842	-0.639	-0.142	-0.373
	[-2.120, -0.205]	[-4.304, -0.451]	[-4.244, 0.560]	[-2.669, 1.391]	[-1.405, 1.120]	[-1.299, 0.553]
9	-1.394*	-2.917*	-2.194	-0.730	-0.642	-0.441
	[-2.678, -0.110]	[-5.668, -0.167]	[-5.456, 1.068]	[-3.065, 1.604]	[-2.262, 0.977]	[-1.878, 0.996]
12	-1.164	-3.047	-1.878	-0.736	-0.070	0.368
	[-2.858, 0.530]	[-6.372, 0.278]	[-5.443, 1.687]	[-3.835, 2.363]	[-2.394, 2.254]	[-1.623, 2.358]
15	-1.082	-2.042	-2.703	-1.837	0.397	1.697
	[-3.197, 1.033]	[-5.054, 0.969]	[-7.176, 1.770]	[-5.677, 2.003]	[-2.706, 3.501]	[-0.983, 4.377]
18	-1.064	-1.902	-2.021	-2.986	-0.237	2.600
	[-3.561, 1.433]	[-5.989, 2.184]	[-5.291, 1.249]	[-8.097, 2.126]	[-4.065, 3.59]	[-1.262, 6.461]
21	-1.141	-1.984	-3.007	-3.339	-0.981	2.087
	[-4.020, 1.737]	[-6.272, 2.305]	[-6.689, 0.674]	[-8.376, 1.699]	[-5.145, 3.184]	[-1.006, 5.180]
24	-0.952	-1.024	-3.051	-2.551	-1.004	1.472
	[-4.258, 2.353]	[-6.648, 4.601]	[-6.899, 0.796]	[-6.923, 1.82]	[-5.904, 3.896]	[-2.758, 5.701]
				Easing Actions		
0	0.049	-0.38	-0.010	0.118	0.173	0.337*
	[-0.109, 0.207]	[-0.868, 0.108]	[-0.248, 0.227]	[-0.102, 0.339]	[-0.071, 0.417]	[0.131, 0.543]
3	0.089	-0.656	-0.246	-0.028	0.671	1.081*
	[-0.341, 0.519]	[-1.821, 0.509]	[-0.997, 0.505]	[-0.741, 0.684]	[-0.078, 1.419]	[0.222, 1.941]
6	0.016	-0.576	-0.078	0.388	0.701*	0.745*
	[-0.562, 0.593]	[-1.731, 0.579]	[-1.304, 1.147]	[-0.805, 1.581]	[0.074, 1.328]	[0.056, 1.434]
9	-0.432	-1.499	-0.715	-0.037	0.677	0.529
	[-1.238, 0.373]	[-3.512, 0.514]	[-2.025, 0.595]	[-1.706, 1.631]	[-0.055, 1.409]	[-0.350, 1.408]
12	-0.568	-1.854	-0.879	0.358	0.533	0.102
	[-1.572, 0.435]	[-4.074, 0.366]	[-2.618, 0.859]	[-1.461, 2.178]	[-0.453, 1.519]	[-1.223, 1.428]
15	-0.739	-1.664	-1.417	0.426	0.567	0.393
	[-1.900, 0.423]	[-3.420, 0.093]	[-3.512, 0.678]	[-2.050, 2.901]	[-0.500, 1.634]	[-1.483, 2.269]
18	-0.967	-2.522 *	-2.432	0.680	0.257	0.704
	[-2.355, 0.421]	[-4.811, -0.234]	[-5.280, 0.416]	[-2.547, 3.906]	[-1.354, 1.868]	[-0.836, 2.243]
21	-1.274	-3.320*	-2.809	-0.122	0.518	0.514
	[-2.794, 0.246]	[-6.393, -0.248]	[-6.406, 0.788]	[-2.841, 2.597]	[-1.236, 2.272]	[-1.297, 2.325]
24	-1.561	-4.000*	-3.394	-0.603	0.407	0.961
	[-3.215, 0.092]	[-7.149, -0.852]	[-7.365, 0.578]	[-3.562, 2.357]	[-2.022, 2.836]	[-0.898, 2.821]

Notes: APE denotes the average policy effects. The first column is months after the actions. * denotes significance at the 95% level. [,] are the 95% bootstrap confidence intervals for the estimator of QPE.

Table 8: QPE Estimates of Macroprudential Policies (Ordered Probit Specification 2)

				Tightening Actions		
	APE	$\tau = 0.1$	$\tau = 0.3$	$\tau = 0.5$	$\tau = 0.7$	$\tau = 0.9$
0	-0.144	-0.166	-0.171	-0.121	-0.060	-0.162
	[-0.330, 0.041]	[-0.619, 0.287]	[-0.540, 0.198]	[-0.461, 0.219]	[-0.433, 0.313]	[-0.483, 0.159]
6	-0.644	-2.268	0.366	0.962	0.281	0.213
	[-1.844, 0.556]	[-4.594, 0.058]	[-3.497,4.229]	[-2.483, 4.407]	[-1.250, 1.813]	[-1.250, 1.675]
12	-0.781	-2.708	-0.708	-0.037	1.521	0.754
	[-2.905, 1.342]	[-6.717, 1.301]	[-5.195, 3.779]	[-3.694, 3.620]	[-2.254, 5.295]	[-1.625, 3.133]
18	-0.796	-0.761	-1.173	0.039	1.447	2.630
	[-3.834, 2.241]	[-5.532, 4.011]	[-4.984, 2.638]	[-4.101, 4.180]	[-3.602, 6.497]	[-0.991, 6.250]
24	-0.701	-0.115	-0.159	0.417	2.710	4.029
	[-4.650, 3.247]	[-6.849, 6.618]	[-5.014, 4.695]	[-3.971, 4.805]	[-3.661, 9.082]	[-0.632, 8.691]
				Easing Actions		
	APE	$\tau = 0.1$	$\tau = 0.3$	$\tau = 0.5$	$\tau = 0.7$	$\tau = 0.9$
0	0.035	-0.330	-0.051	0.118	0.111	0.365*
	[-0.141, 0.211]	[-0.851, 0.190]	[-0.314, 0.212]	[-0.100, 0.337]	[-0.168, 0.390]	[0.051, 0.680]
6	0.102	-0.364	0.195	0.931	0.979*	0.554
	[-0.533, 0.736]	[-1.773, 1.046]	[-0.976, 1.365]	[-0.089, 1.950]	[0.162, 1.797]	[-0.527, 1.634]
12	-0.301	-1.586	-0.434	0.639	0.923	0.270
	[-1.365, 0.764]	[-4.327, 1.154]	[-2.383, 1.515]	[-1.222, 2.500]	[-0.100, 1.946]	[-1.135, 1.675]
18	-0.632	-2.522	-1.895	1.134	1.427	1.260
	[-2.191, 0.926]	[-5.660, 0.615]	[-4.771, 0.981]	[-2.624, 4.892]	[-0.093, 2.947]	[-1.671, 4.191]
24	-1.209	-3.994	-1.711	0.500	0.945	1.173
	[-3.104, 0.685]	[-8.480, 0.492]	[-5.062, 1.640]	[-3.313, 4.313]	[-1.604, 3.494]	[-0.933, 3.280]

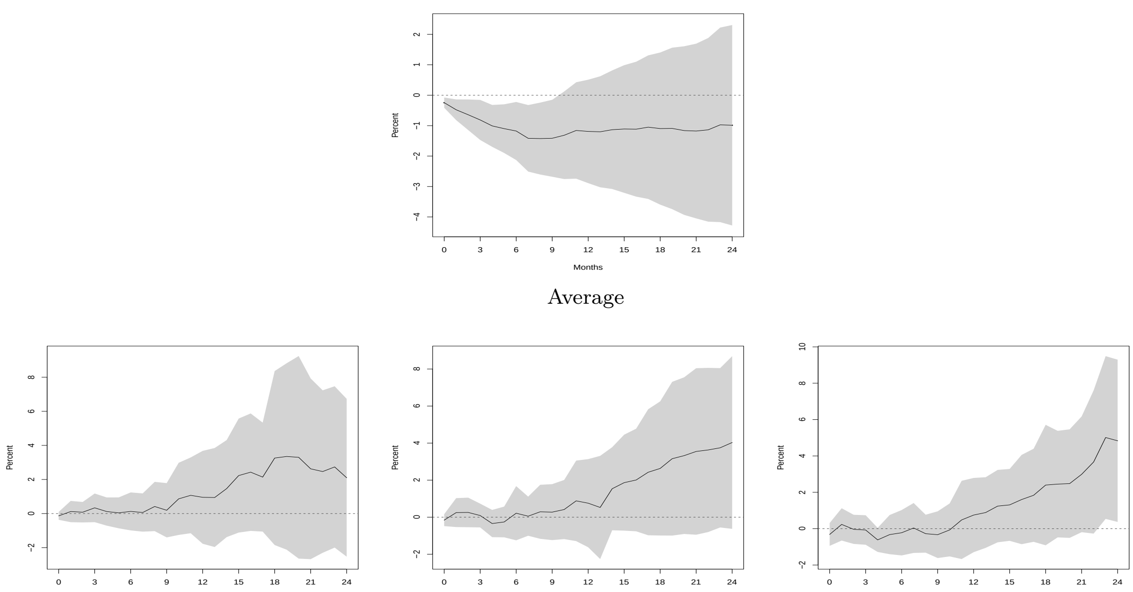
Notes: APE denotes the average policy effects. The first column is months after the actions. * denotes significance at the 95% level. [,] are the 95% bootstrap confidence intervals for the estimator of QPE.

Table 9: QPE Estimates of Macroprudential Policies (Five Categories)

	APE	$\tau = 0.1$	$\tau = 0.3$	$\tau = 0.5$	$\tau = 0.7$	$\tau = 0.9$
			Tightening Actions			
0	-0.258*	-0.022	-0.236	-0.311	-0.190	-0.334*
	[-0.417, -0.098]	[-0.476, 0.431]	[-0.565, 0.092]	[-0.679, 0.056]	[-0.487, 0.106]	[-0.575, -0.094]
3	-0.917*	-1.598*	-1.289	-1.084	-0.480	-0.099
	[-1.531, -0.303]	[-2.623, -0.574]	[-2.647, 0.068]	[-2.43, 0.262]	[-1.489, 0.529]	[-0.844, 0.645]
6	-1.374*	-1.566	-1.856	-0.830	-0.955	-0.657
	[-2.258, -0.489]	[-3.407, 0.275]	[-3.956, 0.244]	[-3.018, 1.358]	[-2.272, 0.362]	[-1.666, 0.352]
9	-1.764*	-1.928	-1.94	-2.156	-1.384	-0.925
	[-2.929, -0.598]	[-4.371, 0.516]	[-4.232, 0.353]	[-4.53, 0.217]	[-3.391, 0.623]	[-2.214, 0.365]
12	-1.507*	-1.429	-2.036	-1.749	-1.79	-0.125
	[-2.983, -0.03]	[-4.158, 1.301]	[-5.082, 1.011]	[-4.253, 0.754]	[-4.449, 0.868]	[-1.687, 1.437]
15	-1.353	-0.136	-2.315	-2.366	-1.032	1.102
	[-3.08, 0.374]	[-2.949, 2.676]	[-5.895, 1.264]	[-5.406, 0.674]	[-3.504, 1.441]	[-1.775, 3.978]
18	-1.437	0.556	-1.889	-3.611	-0.833	1.903
	[-3.357, 0.483]	[-2.635, 3.748]	[-5.302, 1.524]	[-8.695, 1.473]	[-4.515, 2.849]	[-2.104, 5.91]
21	-1.522	0.248	-2.141	-3.235	-1.442	1.449
	[-3.705, 0.66]	[-3.833, 4.328]	[-5.487, 1.205]	[-7.616, 1.146]	[-5.661, 2.776]	[-1.433, 4.331]
24	-1.277	0.564	-2.271	-2.902	-1.683	0.988
	[-3.687, 1.133]	[-4.427, 5.555]	[-5.689, 1.148]	[-6.852, 1.048]	[-6.618, 3.252]	[-2.877, 4.853]
			Easing Actions			
0	0.154	-0.236	0.079	0.164	0.129	0.337*
	[-0.017, 0.325]	[-0.725, 0.253]	[-0.152, 0.310]	[-0.058, 0.386]	[-0.150, 0.408]	[0.092, 0.582]
3	0.298	-0.331	0.247	-0.042	0.569	0.973*
	[-0.151, 0.748]	[-1.552, 0.890]	[-0.506, 0.999]	[-0.829, 0.744]	[-0.064, 1.203]	[0.246, 1.700]
6	0.356	-0.124	0.120	0.597	0.850*	0.404
	[-0.280, 0.993]	[-1.108, 0.861]	[-1.119, 1.359]	[-0.572, 1.765]	[0.110, 1.590]	[-0.212, 1.020]
9	-0.037	-0.814	-0.236	-0.212	0.492	0.240
	[-0.903, 0.829]	[-2.932, 1.305]	[-1.483, 1.011]	[-2.068, 1.644]	[-0.235, 1.220]	[-0.850, 1.330]
12	-0.001	-0.345	-0.528	0.780	0.547	-0.223
	[-1.044, 1.042]	[-2.798, 2.108]	[-2.496, 1.441]	[-1.521, 3.081]	[-0.494, 1.587]	[-1.175, 0.729]
15	-0.005	0.446	-0.465	0.544	0.135	0.250
	[-1.215, 1.204]	[-2.026, 2.918]	[-3.089, 2.159]	[-1.936, 3.024]	[-0.971, 1.241]	[-1.136, 1.635]
18	-0.066	-0.064	-2.191	0.487	-0.139	0.564
	[-1.471, 1.339]	[-2.529, 2.402]	[-6.216, 1.834]	[-1.609, 2.583]	[-2.066, 1.789]	[-0.818, 1.946]
21	-0.371	0.454	-2.721	0.711	0.603	-0.124
	[-1.898, 1.157]	[-2.465, 3.372]	[-7.396, 1.954]	[-1.818, 3.239]	[-1.326, 2.531]	[-0.958, 0.710]
24	-0.593	-1.734	-3.201	-0.155	0.017	0.364
	[-2.186, 1.000]	[-4.572, 1.104]	[-7.874, 1.472]	[-2.528, 2.217]	[-2.603, 2.636]	[-1.351, 2.078]

Notes: APE denotes the average policy effects. The first column is months after the actions. * denotes significance at the 95% level. [,] are the 95% bootstrap confidence intervals for the estimator of QPE.

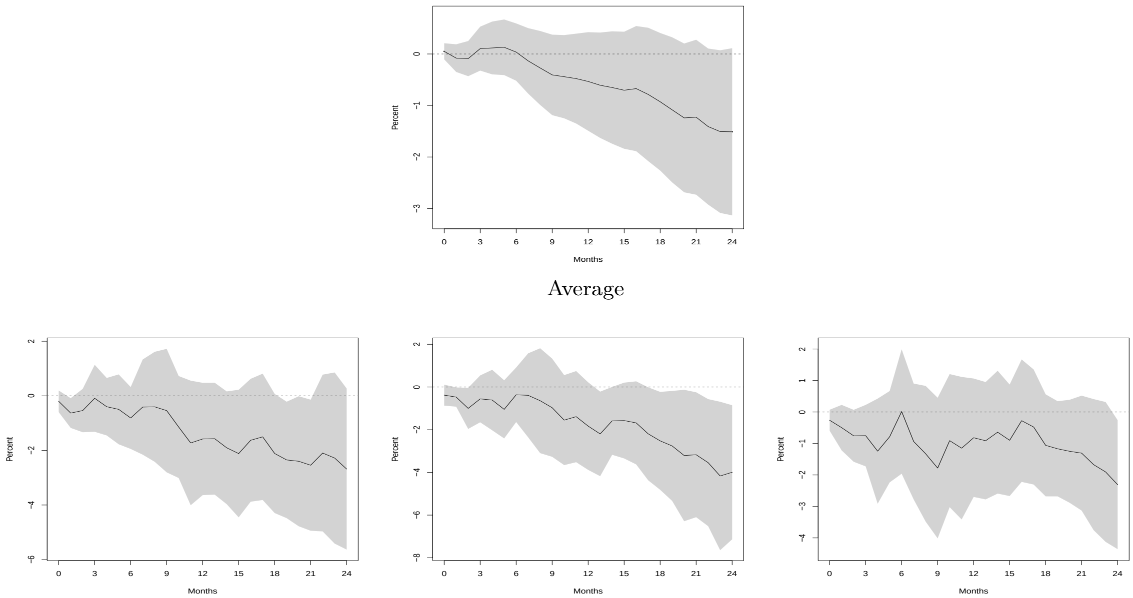
Table 10: Responses of Real Bank Credit to Macroprudential Actions (Period: 1948M2–1983M12)



Average

Quantile ($\tau = 0.85$) Quantile ($\tau = 0.90$) Quantile ($\tau = 0.95$)

Figure 2: Macroprudential Policy Effects: Tightening Actions



Average

Quantile ($\tau = 0.15$) Quantile ($\tau = 0.10$) Quantile ($\tau = 0.05$)

Figure 3: Macroprudential Policy Effects: Easing Actions

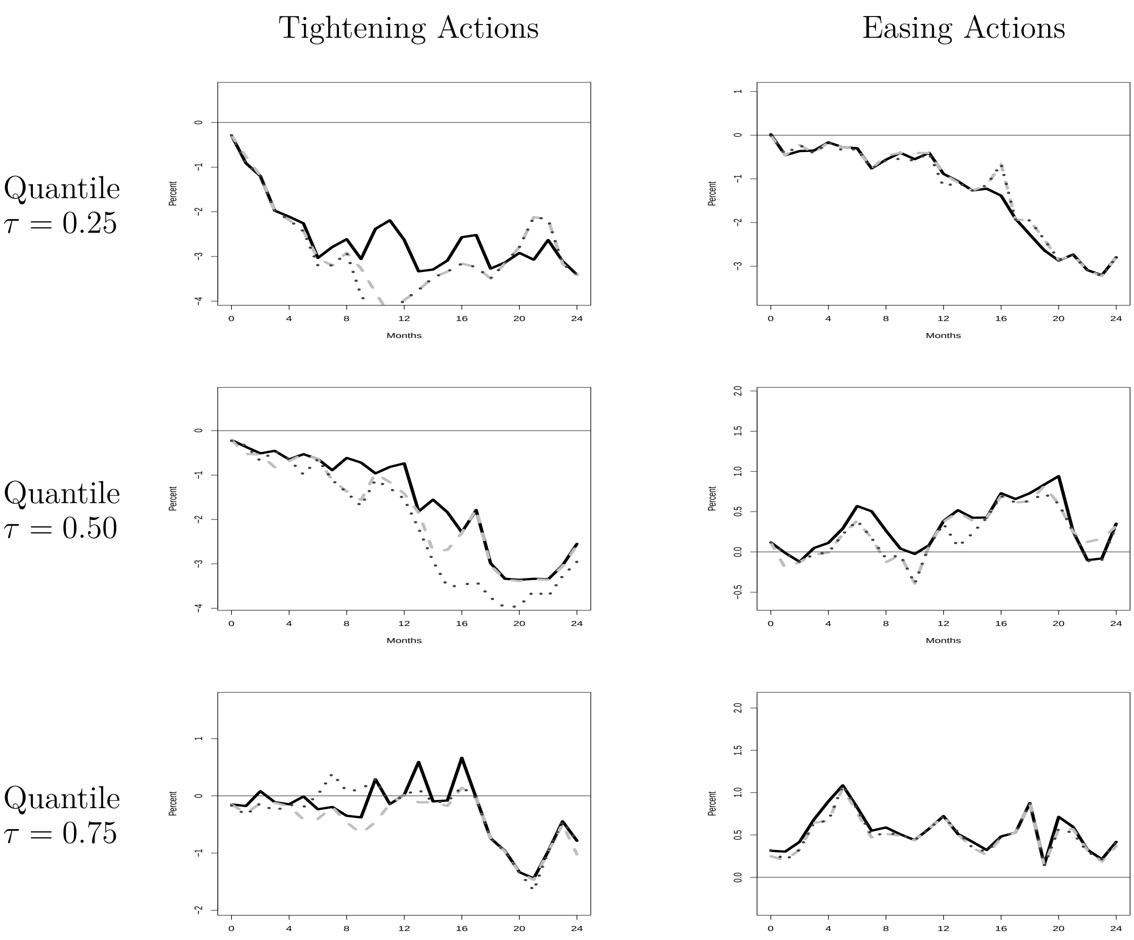


Figure 4: Robustness Check: Different Lags

Supplement to "Quantile Policy Effects: An Application to US Macroprudential Policy"

The supplement appendix outlines all the proof of Lemmas and Theorems in the main paper, the step-by-step implementation procedures for constructing pointwise confidence intervals and confidence bands for quantile policy effects (QPE), and the sensitivity analysis of the unconfoundedness assumption.

1 Lemmas and Theorems

For ease of reference, we repeat some definitions and all assumptions from the main paper. First, define $Y^{\psi}_{t,h}(d)$ as the potential outcome for $d \in \mathcal{D}$. Subsequently, the observed outcomes Y_{t+h} are equal to $Y^{\psi}_{t,h}(d)$ if D_t is equal to d:

$$Y_{t+h} = \sum_{d \in \mathcal{D}} Y^{\psi}_{t,h}(d) \cdot \mathbf{1}\{D_t = d\}. \tag{1}$$

Additionally, let the outcome variable and the policy variable be generated as the following:

$$Y_t = Y(D_t, Z_t, u_t), \quad D_t = D(Z_t, \psi, \varepsilon_t), \tag{2}$$

where u_t and ε_t denote unobserved variables. Then, all assumptions are as follows:

Assumption 1 *(Unconfoundedness) $Y^{\psi}_{t,h}(d_j) \perp D_t | Z_t$ for all $h \geq 0$ and for all d_j, with ψ fixed, $\psi \in \Psi$.*

Assumption 2 *(Overlap) The propensity score function $p^j(Z_t, \psi) > 0$ for all Z_t and for all $j \in \{0, \cdots, J\}$. In addition, $\sum_{j=0}^{J} p^j(Z_t, \psi) = 1$ for all Z_t.*

Assumption 3 *(Structural Model) Assume that*

1. *Y_t and D_t are generated according to (2);*
2. *$\{\varepsilon_t\}_{t=1}^{\infty}$ and $\{u_t\}_{t=1}^{\infty}$ are sequences of i.i.d. random variables;*

3. $\{\varepsilon_t\}_{t=1}^{\infty}$, $\{u_t\}_{t=1}^{\infty}$ and $\{Z'_{e,t}\}_{t=1}^{\infty}$ are jointly independent.

Assumption 4 *(Weak dependence of the data) The stationary sequence χ_t is β-mixing with $\beta_i = O(i^{-q})$ and $q > p/(p-2)$ for some $2 < p < \infty$.*

Assumption 5 *Assume that the parameter $\psi \in \Psi$ where $\Psi \subset \mathbb{R}^{k_\psi}$ is a compact set and the number of covariates $k_\psi < \infty$.*

Assumption 6 *(Parametric Propensity Scores) Assume that for all $j \in \{0, \cdots, J\}$,*

1. $E[\mathbf{1}\{D_t = d_j\}|Z_t] = p_t^j(Z_t, \psi_0)$, and for all $\psi \neq \psi_0$, $E[\mathbf{1}\{D_t = d_j\}|Z_t] \neq p^j(Z_t, \psi)$;

2. for all Z_t, $p^j(Z_t, \psi)$ is differentiable with respect to ψ for $\psi \in N_\delta(\psi_0) \equiv \{\psi \in \Psi | \|\psi - \psi_0\| \leq \delta\}$ and some $\delta > 0$;

3. let $g^j(Z_t, \psi) = 1/p^j(Z_t, \psi)$. $E[\sup_{\psi \in N_\delta(\psi_0)} |g^j(Z_t, \psi_0)|^\varepsilon] \leq M$, $E[\sup_{\psi \in N_\delta(\psi_0)} \|\partial g^j(Z_t, \psi_0)/\partial \psi\|^\varepsilon] \leq M$ and $E[\sup_{\psi \in N_\delta(\psi_0)} \|\partial^2 g^j(Z_t, \psi)/\partial \psi \partial \psi'\|^\varepsilon] \leq M$ with $M < \infty$ and for some $2 < \varepsilon < \infty$.

Assumption 7 *(Asymptotic properties of $\hat{\psi}$) $\sqrt{T}(\hat{\psi} - \psi_0) = T^{-1/2} \sum_{t=1}^{T} \ell(D_t, Z_t, \psi_0) + o_p(1)$ with $E[\|\ell(D_t, Z_t, \psi_0)\|^p] < \infty$, where p is the same as in Assumption 4.*

Assumption 8 *For all $h \geq 0$ and $j \in \{0, \cdots, J\}$,*

1. $Y_{t,h}^{\psi}(d_j)$ has convex and compact supports $[q_j^l, q_j^u]$;

2. $F_j^h(q, \psi)$ is a continuous function on $[q_j^l, q_j^u]$.

Assumption 9 *For all $h \geq 0$ and $j \in \{0, \cdots, J\}$, $f_h^{\psi}(q, d)$ is continuous and bounded away from 0 on $[q_j^l, q_j^u]$.*

Assumption 10 *(Asymptotic properties of $\hat{\psi}^b$) Assume that $\sqrt{T}(\hat{\psi}^b - \psi_0) = T^{-1/2} \sum_{t=1}^{T} \ell(D_t^b, Z_t^b, \psi_0) + o_p(1)$.*

Assumption 11 *(Block size) Assume that $L = C \cdot T^{\rho}$ with $0 < \rho < (p-2)/(2p-2))$ where p is the same as in Assumption 4.*

Lemma 1 *(Identification of distribution functions) Suppose Assumptions 1 and 2 hold. The distribution function $F_j^h(q, \psi)$ can be identified by the observed data as*

$$F_j^h(q, \psi) = E\Big[\frac{\mathbf{1}\{D_t = d_j\} \cdot \mathbf{1}\{Y_{t+h} \leq q\}}{p^j(Z_t, \psi)}\Big].$$

Proof of Lemma 1:

For the specific policy d_j,

$$\begin{aligned}
&E\Big[\frac{\mathbf{1}\{D_t = d_j\}}{p^j(Z_t, \psi)} \cdot \mathbf{1}\{Y_{t+h} \leq q\}\Big] \\
=&E\Big[E\Big[\frac{\mathbf{1}\{D_t = d_j\}}{p^j(Z_t, \psi)} \cdot \mathbf{1}\{Y_{t+h} \leq q\}\Big|Z_t\Big]\Big] \\
=&E\Big[\frac{1}{p^j(Z_t, \psi)} E\Big[\mathbf{1}\{D_t = d_j\} \cdot \mathbf{1}\{Y_{t+h} \leq q\}\Big|Z_t\Big]\Big] \\
=&E\Big[\frac{1}{p^j(Z_t, \psi)} \cdot p^j(Z_t, \psi) \cdot E\Big[\mathbf{1}\{D_t = d_j\} \cdot \mathbf{1}\{Y_{t+h} \leq q\}\Big|Z_t, D_t = d_j\Big]\Big] \\
=&E\Big[E\big[\mathbf{1}\{Y_{t+h} \leq q\}\Big|Z_t, D_t = d_j\big]\Big] \\
=&E\Big[E\big[\mathbf{1}\{Y_{t,h}^{\psi}(d_j) \leq q\}\Big|Z_t, D_t = d_j\big]\Big] \\
=&E\Big[E\big[\mathbf{1}\{Y_{t,h}^{\psi}(d_j) \leq q\}\Big|Z_t\big]\Big] \\
=&F_j^h(q, \psi),
\end{aligned}$$

where the first equality holds by the law of iterated expectations, the third by the law of total probability, the fifth by the potential outcome framework in (1), and the sixth by the unconfoundedness assumption. ∎

Lemma 2 *If Assumption 3 holds, Assumption 1 holds.*

Proof of Lemma 2:

The proof for the case when $Z_t = Z_{e,t}$ is straightforward, so we omit the details. For simplicity, assume that $Z_t = (Y_{t-1}, Z'_{e,t})'$. Note that $Y_t(d) = Y(d, Z_t, u_t)$ and $D_t = D(Z_t, \psi, \varepsilon_t)$, so conditional on Z_t, $Y(d)$ which is a function of u_t is independent of D_t which is a function of ε_t. Next, note that

$$Y_{t+1} = Y(D_{t+1}, Y_t, Z_{e,t+1}, u_{t+1}) = Y(D((Y_t, Z_{e,t+1}, \psi, \varepsilon_{t+1})), Y_t, Z_{e,t+1}, u_{t+1}),$$

and it follows that

$$Y^{\psi}_{t,1}(d) = Y(D((Y_t(d), Z_{e,t+1}, \psi, \varepsilon_{t+1})), Y_t(d), Z_{e,t+1}, u_{t+1}).$$

Then, conditioning on $Z_t = (Y_{t-1}, Z_{e,t})$, we have $Y^{\psi}_{t,1}(d)$ is a function of $Y_t(d)$, $Z_{e,t+1}$, ε_{t+1} and u_{t+1} which are jointly independent of ε_t, so $Y^{\psi}_{t,1}(d)$ is independent of D_t which is a function of ε_t conditioning on Z_t. Similarly,

$$Y_{t+2} = Y(D_{t+2}, Y_{t+1}, Z_{e,t+2}, u_{t+2}) = Y(D((Y_{t+1}, Z_{e,t+2}, \psi, \varepsilon_{t+2})), Y_{t+1}, Z_{e,t+2}, , u_{t+2}),$$

so

$$Y^{\psi}_{t,2}(d) = Y(D((Y^{\psi}_{t,1}(d), Z_{e,t+2}, \psi, \varepsilon_{t+2})), Y^{\psi}_{t,1}(d), Z_{e,t+2}, , u_{t+2}).$$

It follows that conditioning on Z_t, $Y^{\psi}_{t,2}(d)$ is independent of D_t. Then, by induction, the same argument shows that $Y^{\psi}_{t,h}(d)$ is independent of D_t conditioning on Z_t. A similar argument applies to the case when $Z_{y,t}$ is a vector of lagged outcome variables. This completes the proof of Lemma 2. ■

Theorem 1 *(Asymptotic properties of $\hat{F}^h_j(q, \hat{\psi})$) Suppose that Assumptions 1–8 hold. Then,*

$$\sqrt{T}(\hat{F}^h_{\cdot}(\cdot, \hat{\psi}) - F^h_{\cdot}(\cdot, \psi_0)) \Rightarrow \mathcal{F}(\cdot, \cdot),$$

where $\Rightarrow$ denotes weak convergence, and $\mathcal{F}(\cdot, \cdot)$ is a mean-zero Gaussian process with covariance functions,

$$\Omega^{\mathcal{F}}((d_{j_1}, q_1), (d_{j_2}, q_2)) = \lim_{T\to\infty} T^{-1} E\left[\left(\sum_{t=1}^{T} w_{t,d_{j_1}}(q_1, \psi_0)\right)\left(\sum_{t=1}^{T} w_{t,d_{j_2}}(q_2, \psi_0)\right)'\right],$$

where

$$w_{t,d_j}(q,\psi_0) = \big(\mathbf{1}\{Y_{t+h} \le q\} - F_j^h(q,\psi_0)\big)\mathbf{1}\{D_t = d_j\} \cdot g^j(Z_t,\psi_0) + E\Big[\big(\mathbf{1}\{Y_{t+h} \le q\} - F_j^h(q,\psi_0)\big)\mathbf{1}\{D_t = d_j\} \cdot \frac{\partial g^j(Z_t,\psi_0)}{\partial \psi'}\Big]\ell(D_t,Z_t,\psi_0),$$

and $g^j(Z_t,\psi_0) = 1/p^j(Z_t,\psi_0)$.

Proof of Theorem 1:

Let

$$\phi_{t,d_j}(q,\psi_0) = \mathbf{1}\{D_t = d_j\} \cdot \mathbf{1}\{Y_{t+h} \le q\} \cdot g^j(Z_t,\psi_0) - F_j^h(q,\psi_0) + E\Big[\mathbf{1}\{D_t = d_j\} \cdot \mathbf{1}\{Y_{t+h} \le q\} \cdot \frac{\partial g^j(Z_t,\psi_0)}{\partial \psi'}\Big]\ell(D_t,Z_t,\psi_0). \tag{3}$$

Rewrite $\sqrt{T}\tilde{F}_j^h(q,\psi) = T^{-1/2}\sum_{t=1}^T \mathbf{1}\{D_t = d_j\} \cdot \mathbf{1}\{Y_{t+h} \le q\} \cdot g^j(Z_t,\psi)$. Note that

$$\begin{aligned}
&\sqrt{T}(\tilde{F}_j^h(q,\hat\psi) - F_j^h(q,\psi_0))\\
=&\frac{1}{\sqrt{T}}\sum_{t=1}^T \mathbf{1}\{D_t = d_j\} \cdot \mathbf{1}\{Y_{t+h} \le q\} \cdot g^j(Z_t,\psi_0) - F_j^h(q,\psi_0)\\
&+ \frac{1}{T}\sum_{t=1}^T \mathbf{1}\{D_t = d_j\} \cdot \mathbf{1}\{Y_{t+h} \le q\} \cdot \frac{\partial g^j(Z_t,\psi_0)}{\partial \psi'}\sqrt{T}(\hat\psi - \psi_0)\\
&+ \frac{1}{T}\sum_{t=1}^T \mathbf{1}\{D_t = d_j\} \cdot \mathbf{1}\{Y_{t+h} \le q\} \cdot \frac{(\hat\psi - \psi_0)'}{2}\frac{\partial^2 g^j(Z_t,\check\psi)}{\partial \psi' \partial \psi}\sqrt{T}(\hat\psi - \psi_0)\\
=&\frac{1}{\sqrt{T}}\sum_{t=1}^T \mathbf{1}\{D_t = d_j\} \cdot \mathbf{1}\{Y_{t+h} \le q\} \cdot g^j(Z_t,\psi_0) - F_j^h(q,\psi_0)\\
&+ \frac{1}{T}\sum_{t=1}^T \mathbf{1}\{D_t = d_j\} \cdot \mathbf{1}\{Y_{t+h} \le q\} \cdot \frac{\partial g^j(Z_t,\psi_0)}{\partial \psi'}\sqrt{T}(\hat\psi - \psi_0) + o_p(1)\\
=&\frac{1}{\sqrt{T}}\sum_{t=1}^T \mathbf{1}\{D_t = d_j\} \cdot \mathbf{1}\{Y_{t+h} \le q\} \cdot g^j(Z_t,\psi_0) - F_j^h(q,\psi_0)\\
&+ E\Big[\mathbf{1}\{D_t = d_j\} \cdot \mathbf{1}\{y_{t+h} \le q\} \cdot \frac{\partial g^j(Z_t,\psi_0)}{\partial \psi'}\Big]\sqrt{T}(\hat\psi - \psi_0) + o_p(1)\\
=&\frac{1}{\sqrt{T}}\sum_{t=1}^T \mathbf{1}\{D_t = d_j\} \cdot \mathbf{1}\{Y_{t+h} \le q\} \cdot g^j(Z_t,\psi_0) - F_j^h(q,\psi_0)\\
&+ \frac{1}{\sqrt{T}}\sum_{t=1}^T E\Big[\mathbf{1}\{D_t = d_j\} \cdot \mathbf{1}\{Y_{t+h} \le q\} \cdot \frac{\partial g^j(Z_t,\psi_0)}{\partial \psi'}\Big]\ell(D_t,Z_t,\psi_0) + o_p(1)
\end{aligned}$$

$$\equiv \frac{1}{\sqrt{T}} \sum_{t=1}^{T} \phi_{t,d_j}(q, \psi_0) + o_p(1), \tag{4}$$

where $\check{\psi}$ is between ψ_0 and $\hat{\psi}$ and the $o_p(1)$ result holds uniformly over q. The first equality holds by a second-order mean value expansion of $\sqrt{T}\tilde{F}_j^h(q, \hat{\psi})$ around ψ_0. The second equality holds because

$$\begin{aligned}
&\sup_{q\in[q_j^l, q_j^u]} \Big| \frac{1}{T} \sum_{t=1}^{T} \mathbf{1}\{D_t = d_j\} \cdot \mathbf{1}\{y_{t+h} \leq q\} \cdot \frac{(\hat{\psi} - \psi_0)'}{2} \frac{\partial^2 g^j(Z_t, \check{\psi})}{\partial \psi' \partial \psi} \sqrt{T}(\hat{\psi} - \psi_0) \Big| \\
\leq & \sqrt{T} \|\hat{\psi} - \psi_0\|^2 \cdot \frac{1}{T} \sum_{t=1}^{T} \sup_{\psi \in N_\delta(\psi_0)} \Big\| \frac{\partial^2 g^j(Z_t, \psi)}{\partial \psi' \partial \psi} \Big\| = o_p(1) \cdot O_p(1),
\end{aligned}$$

in which $\sqrt{T}\|\hat{\psi} - \psi_0\|^2 = o_p(1)$ and $T^{-1}\sum_{t=1}^{T} \sup_{\psi\in N_\delta(\psi_0)} \big\| \frac{\partial^2 g^j(Z_t,\psi)}{\partial\psi'\partial\psi} \big\| = O_p(1)$ by Assumption 7. The third equality holds because $\{\mathbf{1}\{D_t = d_j\} \cdot \mathbf{1}\{Y_{t+h} \leq q\} \cdot \frac{\partial g^j(Z_t,\psi_0)}{\partial \psi'} : q \in [q_j^l, q_j^u]\}$ is a VC class of functions, and under Assumptions 4 and 6, the functional CLT of Arcones and Yu (1994) implies that

$$\begin{aligned}
\sup_{q\in[q_j^l, q_j^u]} \Big| &\frac{1}{T} \sum_{t=1}^{T} \mathbf{1}\{D_t = d_j\} \cdot \mathbf{1}\{Y_{t+h} \leq q\} \cdot \frac{\partial g^j(Z_t, \psi_0)}{\partial \psi'} \\
&- E\Big[\mathbf{1}\{D_t = d_j\} \cdot \mathbf{1}\{Y_{t+h} \leq q\} \cdot \frac{\partial g^j(Z_t, \psi_0)}{\partial \psi'}\Big] \Big| = o_p(1).
\end{aligned}$$

Under Assumption 7, $\|\hat{\psi} - \psi_0\| = O_p(T^{-1/2})$, so $\sqrt{T}\|\hat{\psi} - \psi_0\|^2 = O_p(T^{-1/2}) = o_p(1)$, and the last equality holds.

By a delta method and (4), we now have

$$\begin{aligned}
&\sqrt{T}\left(\hat{F}_j^h(q, \hat{\psi}) - F_j^h(q, \psi_0)\right) \\
=&\sqrt{T}\left(\tilde{F}_j^h(q, \hat{\psi}) - F_j^h(q, \psi_0)\tilde{F}_j^h(q_j^u, \hat{\psi})\right) + o_p(1) \\
=&\sqrt{T}\left(\tilde{F}_j^h(q, \hat{\psi}) - F_j^h(q, \psi_0)\right) - F_j^h(q, \psi_0)\sqrt{T}\left(\tilde{F}_j^h(q_j^u, \hat{\psi}) - 1\right) + o_p(1) \\
=&\frac{1}{\sqrt{T}} \sum_{t=1}^{T} \phi_{t,d_j}(q, \psi_0) + o_p(1) - F_j^h(q, \psi_0) \frac{1}{\sqrt{T}} \sum_{t=1}^{T} \phi_{t,d_j}(q_j^u, \psi_0) + o_p(1) + o_p(1) \\
\equiv&\frac{1}{\sqrt{T}} \sum_{t=1}^{T} w_{t,d_j}(q, \psi_0) + o_p(1),
\end{aligned}$$

where

$$
\begin{aligned}
w_{t,d_j}(q,\psi_0) =& \phi_{t,d_j}(q,\psi_0) - F_j^h(q,\psi_0)\cdot\phi_{t,d_j}(q^u,\psi_0) \\
=& \big(\mathbf{1}\{Y_{t+h}\le q\} - F_j^h(q,\psi_0)\big)\mathbf{1}\{D_t=d_j\}\cdot g^j(Z_t,\psi_0) \\
&+ E\Big[\big(\mathbf{1}\{Y_{t+h}\le q\} - F_j^h(q,\psi_0)\big)\mathbf{1}\{D_t=d_j\}\cdot\frac{\partial g^j(Z_t,\psi_0)}{\partial\psi'}\Big]\ell(D_t,Z_t,\psi_0).
\end{aligned}
\tag{5}
$$

Note that $\{\mathbf{1}\{Y_{t+h}\le q\}-F_j^h(q,\psi_0) : d_j=1,\dots,J, q\in[q^l,q^u]\}$ is a VC class of functions, and this implies that $\{\mathbf{1}\{D_t=d_j\}(\mathbf{1}\{Y_{t+h}\le q\}-F_j^h(q,\psi_0))\cdot g^j(Z_t,\psi_0) : d_j=1,\dots,J, q\in[q^l,q^u]\}$ is a VC class of functions, and so is each element of $\{E\big[\mathbf{1}\{D_t=d_j\}\cdot(\mathbf{1}\{Y_{t+h}\le q\}-F_j^h(q,\psi_0))\cdot\frac{\partial g^j(Z_t,\psi_0)}{\partial\psi'}\big] : d_j=1,\dots,J, q\in[q^l,q^u]\}$. This further implies that $\{E\big[\mathbf{1}\{D_t=d_j\}\cdot(\mathbf{1}\{Y_{t+h}\le q\}-F_j^h(q,\psi_0))\cdot\frac{\partial g^j(Z_t,\psi_0)}{\partial\psi'}\big]\cdot\ell(D_t,Z_t,\psi_0) : d_j=1,\dots,J, q\in[q^l,q^u]\}$ is a VC class of functions. It then follows that $\{w_{t,d_j}(q,\psi_0) : j=1,\dots,J, q\in[q^l,q^u]\}$ is a VC class of functions. By the functional CLT of Arcones and Yu (1994), $T^{-1/2}\sum_{t=1}^T w_{t,d_j}(q,\psi_0)$ obeys the functional CLT and weakly converges to a Gaussian process $\mathcal{F}_(\cdot,\cdot)$ with mean zero and covariance functions $\Omega^{\mathcal{F}}((d_{j1},q_1),(d_{j2},q_2))$. It then follows that $\sqrt{T}(\hat{F}_j^h(q,\hat{\psi})-F_j^h(q,\psi_0))$ weakly converges to a Gaussian process $\mathcal{F}_(\cdot,\cdot)$. ■

Theorem 2 *(Asymptotic properties of $\hat{Q}_j^h(\tau,\hat{\psi})$) Suppose that Assumptions 1–9 hold. Then,*

$$\sqrt{T}(\hat{Q}^h_{\cdot}(\cdot,\hat{\psi})-Q^h_{\cdot}(\cdot,\psi_0)) \Rightarrow \mathcal{Q}(\cdot,\cdot),$$

where $\mathcal{Q}(\cdot,\cdot)$ is a mean-zero Gaussian process with covariance functions,

$$\Omega^{\mathcal{Q}}((d_{j1},\tau_1),(d_{j2},\tau_2)) = \lim_{T\to\infty} T^{-1}E\left[\left(\sum_{t=1}^T w^Q_{t,d_{j1}}(\tau_1,\psi_0)\right)\left(\sum_{t=1}^T w^Q_{t,d_{j2}}(\tau_2,\psi_0)\right)'\right],$$

where

$$w^Q_{t,d_j}(\tau,\psi_0) = -\frac{w_{t,d_j}(Q_j^h(\tau,\psi_0),\psi_0)}{f_h^{\psi}(Q_j^h(\tau,\psi_0),d_j)},$$

with $w_{t,d_j}(\cdot,\psi)$ defined in Theorem 1.

Proof of Theorem 2:

Given Assumption 9, and given that the quantile map is Hadamard differentiable, the result follows when we apply the functional delta method.

$$\sqrt{T}[\hat{Q}_j^h(\tau, \hat{\psi}) - Q_j^h(\tau, \psi_0)]$$
$$= -\frac{1}{f_h^{\psi}(Q_j^h(\tau, \psi_0), d_j)} \frac{1}{\sqrt{T}} \sum_{t=1}^{T} w_{t,d_j}(Q_j^h(\tau, \psi_0), \psi_0) + o_p(1).$$

See Lemma 3.9.23 and Example 3.9.24 of van der Vaart and Wellner (1996, pp. 386-387).

■

Theorem 3 *(Asymptotic properties of $\hat{\Delta}_{\cdot}^h(\cdot, \hat{\psi})$) Suppose that Assumptions 1–9 hold. Then,*

$$\sqrt{T}(\hat{\Delta}_{\cdot}^h(\cdot, \hat{\psi}) - \Delta_{\cdot}^h(\cdot, \psi_0)) \Rightarrow \mathcal{R}(\cdot, \cdot),$$

where $\mathcal{R}(\cdot, \cdot)$ is a mean-zero Gaussian process with covariance functions,

$$\Omega_j^{\mathcal{R}}((d_{j_1}, \tau_1), (d_{j_2}, \tau_2)) = \lim_{T \to \infty} T^{-1} E\left[\left(\sum_{t=1}^{T} w_{t,d_{j_1}}^{\Delta}(\tau_1; \psi_0)\right)\left(\sum_{t=1}^{T} w_{t,d_{j_2}}^{\Delta}(\tau_2; \psi_0)\right)'\right],$$

where

$$w_{t,d_j}^{\Delta}(\tau; \psi_0) = -\left[\frac{w_{t,d_j}(Q_j^h(\tau, \psi_0), \psi_0)}{f_h^{\psi}(Q_j^h(\tau, \psi_0), d_j)} - \frac{w_{t,d_0}(Q_0^h(\tau, \psi_0), \psi_0)}{f_h^{\psi}(Q_0^h(\tau, \psi_0), d_0)}\right],$$

with $w_{t,d_j}(\cdot, \psi)$ defined in Theorem 1.

Proof of Theorem 3:

The QPE is the difference between specific quantiles of the potential outcomes of policies d_j and d_0 in the following:

$$\Delta_j^h(\tau, \psi_0) = Q_j^h(\tau, \psi_0) - Q_0^h(\tau, \psi_0).$$

The estimator of QPE is the difference between sample quantile functions of the potential outcomes, which is

$$\hat{\Delta}_j^h(\tau, \hat{\psi}) = \hat{Q}_j^h(\tau, \hat{\psi}) - \hat{Q}_0^h(\tau, \hat{\psi}).$$

Under the same Assumptions of Theorems 1 and 2, we have

$$
\begin{aligned}
&\sqrt{T}\big(\hat{\Delta}_j^h(\tau,\hat{\psi}) - \Delta_j^h(\tau,\psi_0)\big)\\
&= \sqrt{T}[\hat{Q}_j^h(\tau,\hat{\psi}) - \hat{Q}_0^h(\tau,\hat{\psi}) - Q_j^h(\tau,\psi_0) + Q_0^h(\tau,\psi_0)]\\
&= \sqrt{T}[\hat{Q}_j^h(\tau,\hat{\psi}) - Q_j^h(\tau,\psi_0)] - \sqrt{T}[\hat{Q}_0^h(\tau,\hat{\psi}) - Q_0^h(\tau,\psi_0)]\\
&= -\frac{1}{\sqrt{T}}\sum_{t=1}^{T} w_{t,d_j}^{\Delta}(\tau;\psi_0) + o_p(1),
\end{aligned}
$$

where

$$
w_{t,d_j}^{\Delta}(\tau;\psi_0) = -\left[\frac{w_{t,j}(Q_j^h(\tau,\psi_0),\psi_0)}{f_h^{\psi}(Q_j^h(\tau,\psi_0),d_j)} - \frac{w_{t,j}(Q_0^h(\tau,\psi_0),\psi_0)}{f_h^{\psi}(Q_0^h(\tau,\psi_0),d_0)}\right].
$$

■

Theorem 4 *Suppose that Assumptions 1–11 hold. Then, conditional on the sample path with probability approaching one,*

$$
\begin{aligned}
&\sqrt{T}(\hat{F}_{\cdot}^{h,b}(\cdot,\hat{\psi}^b) - \hat{F}_{\cdot}^{h}(\cdot,\hat{\psi})) \Rightarrow \mathcal{F}(\cdot,\cdot),\\
&\sqrt{T}(\hat{Q}_{\cdot}^{h,b}(\cdot,\hat{\psi}^b) - \hat{Q}_{\cdot}^{h}(\cdot,\hat{\psi})) \Rightarrow \mathcal{Q}(\cdot,\cdot),\\
&\sqrt{T}(\hat{\Delta}_{\cdot}^{h,b}(\cdot,\hat{\psi}^b) - \hat{\Delta}_{\cdot}^{h}(\cdot,\hat{\psi})) \Rightarrow \mathcal{R}(\cdot,\cdot),
\end{aligned}
$$

where $\mathcal{F}(\cdot,\cdot)$, $\mathcal{Q}(\cdot,\cdot)$, and $\mathcal{R}(\cdot,\cdot)$ are given in Theorems 1–3.

Proof of Theorem 4:

We prove the results associated with the distribution function because the arguments for other cases are similar. Note that by the same arguments of Theorem 1 and with Assumption 10, we can show that

$$
\sqrt{T}\left(\hat{F}_j^{h,b}(q,\hat{\psi}^b) - F_j^h(q,\psi_0)\right) = \frac{1}{\sqrt{T}}\sum_{t=1}^{T} w_{t,d_j}^b(q,\psi_0) + o_p(1),
$$

where

$$
\begin{aligned}
w_{t,d_j}^b(q,\psi_0) =& \big(\mathbf{1}\{Y_{t+h}^b \le q\} - F_j^h(q,\psi_0)\big)\mathbf{1}\{D_t^b = d_j\}\cdot g^j(Z_t^b,\psi_0)\\
&+ E\Big[\big(\mathbf{1}\{Y_{t+h}^b \le q\} - F_j^h(q,\psi_0)\big)\mathbf{1}\{D_t^b = d_j\}\cdot\frac{\partial g^j(Z_t,\psi_0)}{\partial\psi'}\Big]\ell(D_t^b,Z_t^b,\psi_0).
\end{aligned}
$$

We then have

$$\sqrt{T}\left(\hat{F}_j^{h,b}(q,\hat{\psi}^b)-\hat{F}_j^{h}(q,\hat{\psi})\right)=\frac{1}{\sqrt{T}}\sum_{t=1}^{T}w_{t,d_j}^b(q,\psi_0)-\frac{1}{\sqrt{T}}\sum_{t=1}^{T}w_{t,d_j}(q,\psi_0)+o_p(1),$$

and by Theorem 2.5 of Radulović (2002), we have conditionally on the sample path with probability approaching one,

$$\frac{1}{\sqrt{T}}\sum_{t=1}^{T}w_{t,d_j}^b(q,\psi_0)-\frac{1}{\sqrt{T}}\sum_{t=1}^{T}w_{t,d_j}(q,\psi_0)\Rightarrow\mathcal{F}(\cdot,\cdot).$$

Therefore, it follows conditional on the sample path with probability approaching one that $\sqrt{T}[\hat{F}_{\cdot}^{h,b}(\cdot,\hat{\psi}^b)-\hat{F}_{\cdot}^{h}(\cdot,\hat{\psi})]\Rightarrow\mathcal{F}(\cdot,\cdot)$. ■

2 Implementation Procedures for Pointwise Intervals and Confidence Bands

The implementation procedure for constructing pointwise confidence intervals for QPE can be summarized as follows:

Implementation Procedure of Confidence Interval for QPE

1. Define the sample size as T and the length of the blocks as $L=C\cdot T^{\rho}$. There are $T-L+1$ different overlapping blocks, and the j-th block is denoted as $\{(Y_{t+h},Y_t,Z_t,D_t)\}_{t=j}^{j+L}$ for $j=1,\cdots,T-L+1$.

2. Determine the smallest natural number, N, such that $N\cdot L\geq T$. Obtain a bootstrap sample by randomly sampling N blocks with replacement from the available $T-L+1$ blocks and lay them end-to-end in the order sampled. Discard the last $NL-T$ observations from the last sampled block.

3. For each bootstrap sample $b=1,\cdots,B$, compute the propensity score function $\hat{p}_j^b(z_t,\hat{\psi}^b)$, the quantile functions $\hat{Q}_j^{h,b}(\tau,\hat{\psi}^b)$ and $\hat{Q}_0^{h,b}(\tau,\hat{\psi}^b)$, and then calculate the QPE estimates $\hat{\Delta}_j^{h,b}(\tau,\hat{\psi}^b)=\hat{Q}_j^{h,b}(\tau,\hat{\psi}^b)-\hat{Q}_0^{h,b}(\tau,\hat{\psi}^b)$.

4. For each b, compute $\hat{q}_{j,b} = \sqrt{T}\big|\hat{\Delta}_j^{h,b}(\tau, \hat{\psi}^b) - \hat{\Delta}_j^h(\tau, \hat{\psi})\big|$ and collect $\{\hat{q}_{j,b} : b = 1, \ldots, B\}$. Let $\hat{q}_{j,(a)}$ denote the (a)-th largest element in $\{\hat{q}_{j,b} : b = 1, \ldots, B\}$, and $\lfloor c \rfloor$ denotes the largest integer smaller than or equal to c. Define $\hat{q}_{j,(\lfloor(1-\alpha)*B\rfloor)}$ as the α-th quantile of $\{\hat{q}_{j,b} : b = 1, \ldots, B\}$.

5. Then, the two-sided $1 - \alpha$ confidence interval of the estimator of QPE is given as follows:

$$\Big(\hat{\Delta}_j^h(\tau, \hat{\psi}) - \frac{\hat{q}_{j,(\lfloor(1-\alpha)*B\rfloor)}}{\sqrt{T}},\ \hat{\Delta}_j^h(\tau, \hat{\psi}) + \frac{\hat{q}_{j,(\lfloor(1-\alpha)*B\rfloor)}}{\sqrt{T}}\Big).$$

6. In addition, for each b, compute $\tilde{q}_{j,b} = \sqrt{T}\big[\hat{\Delta}_j^{h,b}(\tau, \hat{\psi}^b) - \hat{\Delta}_j^h(\tau, \hat{\psi})\big]$ and collect $\{\tilde{q}_{j,b} : b = 1, \ldots, B\}$. Let $\tilde{q}_{j,(a)}$ denote the (a)-th largest element in $\{\tilde{q}_{j,b} : b = 1, \ldots, B\}$. Define $\tilde{q}_{j,(\lfloor(1-\alpha)*B\rfloor)}$ as the α-th quantile of $\{\tilde{q}_{j,b} : b = 1, \ldots, B\}$. Then, the one-sided $1 - \alpha$ confidence interval of the estimator of QPE is given as follows:

$$\Big(\hat{\Delta}_j^h(\tau, \hat{\psi}) - \frac{\tilde{q}_{(j,\lfloor(1-\alpha)*B\rfloor)}}{\sqrt{T}},\ \infty\Big) \text{ or } \Big(-\infty,\ \hat{\Delta}_j^h(\tau, \hat{\psi}) + \frac{\tilde{q}_{j,(\lfloor\alpha*B\rfloor)}}{\sqrt{T}}\Big).$$

Next, we summarize the implementation procedure for the confidence band of QPE for $\tau \in [\tau_\ell, \tau_u]$.

Implementation Procedure of Confidence Band for QPE

1. Define the sample size as T and the length of the blocks as $L = C \cdot T^\rho$. There are $T - L + 1$ different overlapping blocks, and the j-th block is $\{(Y_{t+h}, Y_t, Z_t, D_t)\}_{t=j}^{j+L}$ for $j = 1, \cdots, T - L + 1$.

2. Determine the smallest natural number, N, such that $N \cdot L \geq T$. Obtain a bootstrap sample by randomly sampling N blocks with replacement from the available $T - L + 1$ blocks and lay them end-to-end in the order sampled. Discard the last $NL - T$ observations from the last sampled block.

3. For each bootstrap sample $b = 1, \cdots, B$, compute the propensity score function $\hat{p}_j^b(z_t, \hat{\psi}^b)$. Define a grid with $K+1$ evenly spaced points $\tau \in [\tau_\ell, \tau_\ell + u, , \dots, \tau_u - u, \tau_u]$, where $u = (\tau_u - \tau_\ell)/K$. Calculate the quantile functions $\hat{Q}_j^{h,b}(\tau, \hat{\psi}^b)$ and $\hat{Q}_0^{h,b}(\tau, \hat{\psi}^b)$ for each τ in the grid, and then compute the QPE estimates $\hat{\Delta}_j^{h,b}(\tau, \hat{\psi}^b) = \hat{Q}_j^{h,b}(\tau, \hat{\psi}^b) - \hat{Q}_0^{h,b}(\tau, \hat{\psi}^b)$.

4. For each b, compute $\hat{w}_{j,b} = \sqrt{T} \max_{k \in \{0,\dots,K\}} \left| \hat{\Delta}_j^{h,b}(\tau_\ell + k \cdot u, \hat{\psi}^b) - \hat{\Delta}_j^h(\tau_\ell + k \cdot u, \hat{\psi}) \right|$ and collect $\{\hat{w}_{j,b} : b = 1 \dots, B\}$.

5. Define $\hat{w}_{j,(\lfloor (1-\alpha) * B \rfloor)}$ as the α-th quantile of t $\{\hat{w}_{j,b} : b = 1 \dots, B\}$. Then, the two-sided uniform $1 - \alpha$ confidence band of the estimator of QPE is given as follows:

$$\left\{ \left(\hat{\Delta}_j^h(\tau, \hat{\psi}) - \frac{\hat{w}_{j,(\lfloor (1-\alpha) * B \rfloor)}}{\sqrt{T}},\ \hat{\Delta}_j^h(\tau, \hat{\psi}) + \frac{\hat{w}_{j,(\lfloor (1-\alpha) * B \rfloor)}}{\sqrt{T}} \right) :\ \tau \in [\tau_\ell, \tau_u] \right\}.$$

3 Sensitivity Analysis of the Unconfoundedness Assumption

Although the unconfoundedness assumption (Assumption 1) is central to our paper, verifying it can be intricate. Tests such as those proposed by Angrist and Kuersteiner (2011) involve complex computations, making them impractical for our study. Therefore, this section focuses on providing an empirical justification for this assumption. Section 3.1 in the main paper discusses conditioning variables and employs these to estimate the propensity score model. Assumption 1 assumes no unobserved or omitted variables to influence treatment assignment and outcome once observed covariates are considered. To address this, we employ sensitivity analyses to evaluate the potential impacts of omitted variables on our results.[1]

[1]Forbes, Fratzscher, and Straub (2015) and Kuvshinov and Zimmermann (2019) also apply similar methodologies when assessing the effects of omitted variables.

To assess the sensitivity of our results to potential violations of the unconfoundedness assumption due to omitted variables, we consider five variables that may be related to both macroprudential policy and bank credit but are not included in our model. First, we examine the variables for banking crises and stock market crashes from Reinhart and Rogoff (2011). A banking crisis refers to widespread failure or instability in the banking sector, leading to financial distress, liquidity problems, and systemic risks. It can have severe consequences, such as credit crunches, economic contractions, and loss of confidence in the financial system. Similarly, a stock market crash signifies a sudden and significant decline in stock prices across a wide range of companies or the entire market, with potential repercussions for the financial system and overall economic stability. These events can expose vulnerabilities that require regulatory intervention through macroprudential policy.

Second, we consider other macroeconomic variables, including unemployment and long-term interest rates (10-year treasury securities yield). High unemployment levels can indicate economic slowdown and financial instability, prompting the implementation of macroprudential policies to mitigate risks. Long-term interest rates influence investment decisions, borrowing costs, and financial conditions. When these rates are high, they can impact loan affordability, credit demand, and investment. In response, the macroprudential policy may adjust regulations or implement measures to ensure financial system stability. Third, we examine the variable of stock prices from Shiller (2016). Movements in stock prices, especially significant declines, can erode investor confidence and potentially trigger broader financial market instability. In such situations, macroprudential policy may be employed to address the risks associated with market volatility and ensure the financial system's resilience. These variables can potentially affect macroprudential policy decisions and bank credit; therefore, we analyze their impact on our results.

We conduct a series of sensitivity analyses by gradually incorporating the omitted variables into the benchmark model. First, we add one omitted variable at a time, then two, and finally, three variables. We examine the QPE impulse responses with and without these variables, focusing on the 0.1-th, 0.5-th, and 0.90-th quantiles. Figure 1 displays the results for one variable, Figure 2 for two variables, and Figure 3 for three variables. In Figure 1, the black line represents the QPE results for the benchmark model. By contrast, the red, blue, green, and gray dotted lines represent the QPE results when incorporating banking crises, stock market crashes, unemployment, and long-term interest rates, respectively. Interestingly, all four impulse responses are closely aligned and show no significant differences between the results with and without the omitted variables.

Moving to Figure 2, we examine the QPE results for the benchmark model with the inclusion of different combinations of two omitted variables: (1) banking crises and stock market crash, (2) banking crises and unemployment, (3) stock market crash and unemployment, and (4) long-term interest rate and stock price. Similarly, all four impulse responses remain remarkably similar, indicating minimal discrepancies between the results with and without these omitted variables. Figure 3 delves into the QPE results for the benchmark model with the inclusion of three omitted variables: (1) banking crises, stock market crash, and unemployment, (2) stock market crash, unemployment, and long-term interest rates, (3) banking crises, stock market crash, and unemployment, and (4) unemployment, long-term interest rate, and stock price. Once again, the impulse responses demonstrate striking similarity across all four scenarios, suggesting that the presence or absence of these omitted variables has a limited impact on the results. Our sensitivity analyses show that our empirical findings remain robust across different model specifications. The inclusion of various omitted variables does not significantly alter the outcomes. Consequently, our empirical evidence supports the validity of the underlying assumption.

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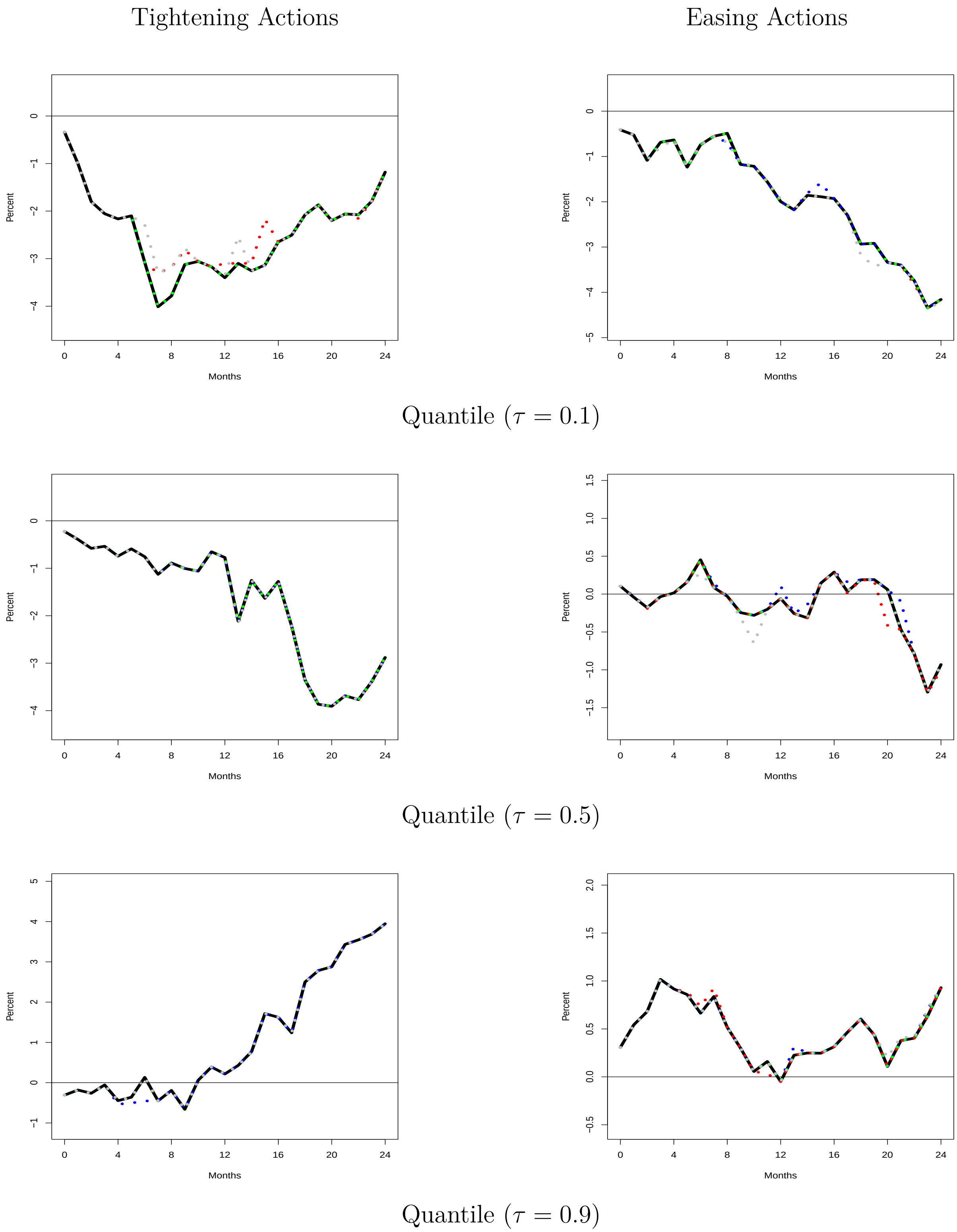

Figure 1: Sensitivity Analyses: One Omitted Variable

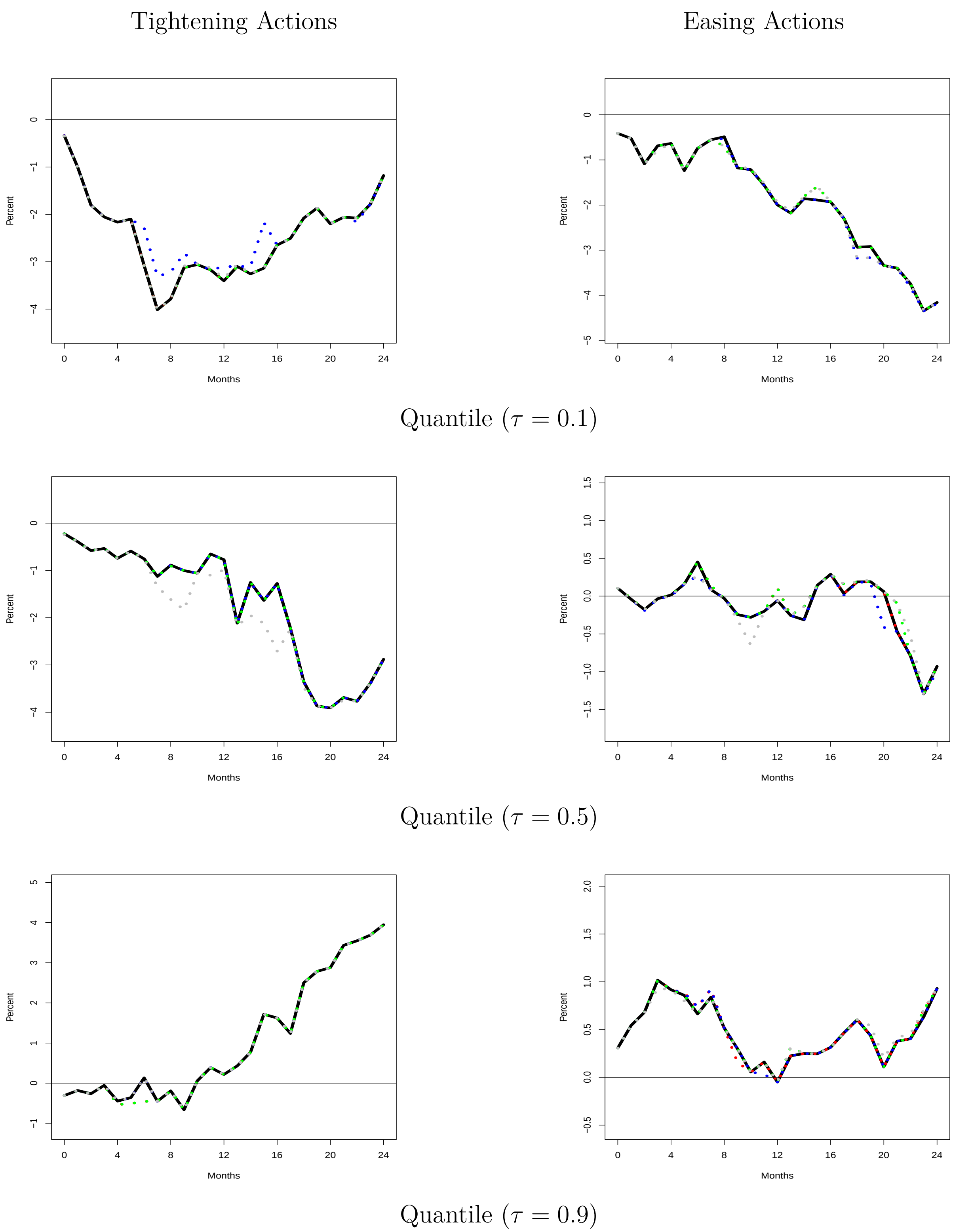

Figure 2: Sensitivity Analyses: Two Omitted Variables

Tightening Actions Easing Actions

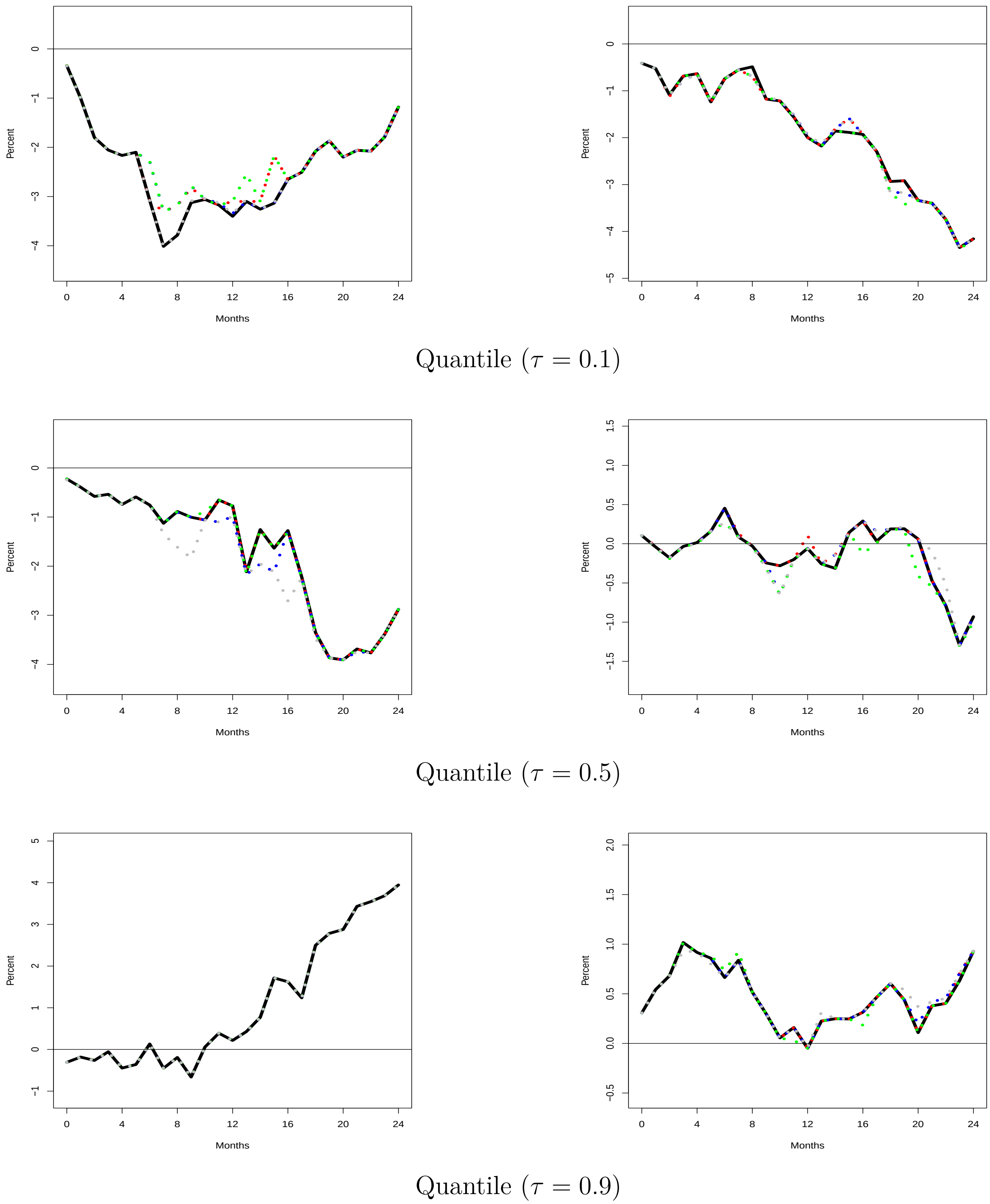

Figure 3: Sensitivity Analyses: Three Omitted Variables