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Conventional and unconventional shadow rates and the US state-level stock returns: Evidence from non-stationary heterogeneous panels

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A B S T R A C T

This study analyzes how monthly stock returns in the United States react to conventional and unconventional shadow rates from February 1994 to April 2023. The study uses a nonstationary heterogeneous panel data technique appropriate for analyzing large cross-sections and long periods. The analysis is separated into turbulent and tranquil periods. The findings suggest that, although the shadow rate is expected to align with the long-term rate, its ability to boost economic activity in the stock markets is only applicable in the short term. Despite the Federal Funds Rate (FFR) being unable to be lowered below zero bounds, the study shows results that support the effectiveness of the FFR in stimulating stock returns in the long run, particularly during crisis periods. The study also reveals that both conventional and unconventional shadow rates share a common feature, which is that they demonstrate how the stock markets can be downward-sticky in the long run with a rising shadow rate in virtually all 50 states in the U.S. The findings provide sturdy insights into the usefulness of unconventional monetary policy measures for stock market performance during crises and normal periods.

1. Introduction

The stock markets worldwide are generally acknowledged as a barometer of the economy, and their dynamics have continuously been closely monitored not only by investors in the markets but also by policymakers. As a result, when the markets were severely affected by the 2007–2009 global financial crisis (GFC), central banks across the globe had to react to mitigate the impact and restore the market's confidence and stability (Aslam et al., 2023). In the context of the U.S. economy, for example, the Fed reacted conventionally by lowering the Fed rate but had to complement it with unconventional monetary policy (UMP) measures due to the limited scope of further cuts in the conventional policy rate. In recent times, the advent of COVID-19 has further deepened the implementation of various UMP measures, thus reawakening concern over how to correctly measure the stance of monetary policy when policy interest rates reach the zero lower bound (ZLB). For instance, UMP measures such as quantitative easing (QE) tend to pose a challenge for econometric analysis, and that is because there is no single policy instrument whose variation reflects unconventional policy steps. A notable effort in this regard is the concept of shadow rates, a prominent measure of the various unconventional monetary policy actions in a single framework.

As introduced by Black (1995), the shadow rate is an unobserved short-term interest rate consistent with longer-term rates that would have prevailed had the interest rate lower bound not been binding (see Krippner, 2014; Wu & Xia, 2016, 2020). As described herein, the shadow rate is characterised by a zero lower bound (ZLB) constraint. This has been the standard assumption in the literature when modelling with shadow rate until recently when De Rezende and Ristiniemi (2023) deviated from the norm and developed a variant of shadow rate that does not impose a lower bound constraint. What is, however, not clear and largely unexplored is whether the assumption of ZLB matters in the first place. Rather than taking sides arbitrarily with any of these approaches to shadow rate, this study aims to test whether a parameter of economic performance, such as stock returns, reacts differently to the varying assumptions about shadow rate. Thus, the following highlights the contributions of this study to the literature, where the ZLB-based shadow rate, which has been standard in the literature, is labelled the conventional shadow rate (CSR). In contrast, the non-ZLB shadow rate of De Rezende and Ristiniemi (2023) is treated as the unconventional

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Table 1
Summary Statistics.

	Full Sample [FS]	Turbulent Periods [TUP]	Tranquil Periods [FS Less TUP]	CMP Period	UMP Period
Panel A: Stock Returns					
Mean	0.0089	0.0079	0.0127	0.0116	0.0085
Std. Dev.	0.0604	0.0801	0.0693	0.0583	0.0540
Max.	0.7444	3.3550	2.3267	0.7444	0.4477
Min.	-0.7988	0.3530	-0.7988	-0.7988	-0.5162
No. Obs.	17500	4950	11900	8950	8600
Panel B: Fed Fund Rate (FFR)					
Mean	2.4660	3.3573	2.2032	4.1941	0.8450
Std. Dev.	2.1673	2.2829	2.0169	1.7267	1.0422
Max.	6.5000	6.5000	6.0000	6.5000	5.1842
Min.	0.2500	0.2500	0.2500	1.0000	0.2500
No. Obs.	17500	4950	11900	8950	8600
Panel C: Conventional Shadow Rate (CSR)					
Mean	2.0104	3.1395	1.6339	4.1065	-0.0181
Std. Dev.	2.6888	2.6192	2.6213	1.8060	1.8432
Max.	7.1170	6.6468	7.1170	7.1170	5.5507
Min.	-2.9856	-1.9983	-2.9856	0.6747	-2.9856
No. Obs.	17500	4950	11900	8950	8600
Panel D: Unconventional Shadow Rate (USR)					
Mean	1.1510	2.3839	0.9211	3.8705	-1.6791
Std. Dev.	3.4727	3.5923	3.3188	1.7809	2.3671
Max.	6.3897	6.3897	6.3102	6.3897	6.3102
Min.	-3.5988	-3.5988	-3.5488	-2.0755	-3.5988
No. Obs.	17500	4950	11900	8950	8600
Panel E: Exchange Rates					
Mean	0.8501	0.8780	0.8450	0.8842	0.8328
Std. Dev.	0.1127	0.1236	0.1047	0.1268	0.0812
Max.	1.1821	1.1778	1.1821	1.1821	1.0201
Min.	0.6341	0.6341	0.6754	0.6834	0.6663
No. Obs.	17500	4950	11900	8950	8600
Panel F: Inflation (Consumer Price Index)					
Mean	89.0088	93.5249	87.0353	74.0042	103.7608
Std. Dev.	16.5884	20.7819	14.5131	7.4170	9.1470
Max.	127.7680	127.7680	108.6000	88.7000	127.7680
Min.	62.1000	68.2000	62.1000	62.1000	90.9000
No. Obs.	17500	4950	11900	8950	8600

Note: Std. Dev. is the standard deviation, Min and Max denote the minimum and maximum values, while Obs. is the number of observations. The CMP and UMP in the last two columns defined the period of conventional and unconventional monetary policy, respectively.

shadow rate (USR).

To begin with, since the pioneering work of Black (1995), there have been growing efforts to improve the accuracy of shadow rates, leading to a number of alternative formulations of shadow rates with consideration for a constant or time-varying lower bound constraint for interest rates (see Krippner, 2014; Kortela, 2016; Bauer & Rudebusch, 2016; Lemke & Vladu, 2016; Wu & Xia, 2016, 2020), and in some instances, a dynamic factor to cater for missing observations (Lombardi & Zhu, 2018). Despite sharing similarities to all of these existing measures of shadow rates in terms of the need to accurately inform about the overall stance of monetary policy, De Rezende and Ristiniemi (2023) deviate from the restrictive assumption of shadow rates with a zero lower bound constraint. Instead, they proposed a variant of shadow rate that can measure the overall stance of monetary policy at any time and not only when the lower bound is a binding constraint for interest rates. Therefore, rather than assigning an arbitrary preference to a specific measure of shadow rates, the first contribution of this study is to test the possibility of stock markets responding differently to the ZLB-based shadow rate (CSR) compared to the shadow rate that does not impose any lower bound constraint (the unconventional shadow rate [USR].

Secondly, we explore the state-level dynamics of the U.S. economy to account for the probable heterogeneity in the stock market behaviour of a country with federating features. This, in particular, is possible in a geographically diverse economy characterised by varying intensities of economic activity across different sectors. More importantly, while the estimation technique employed is capable of accounting for any inherent differences across states in stock prices, it is instructive that we further generate individual results for each state for robustness. The motivation is to consistently circumvent what would otherwise be masked by the aggregate stock index data, thereby undermining the predictability of the stock market (see Salisu et al., 2020a). Studies by Boudoukh et al. (1994), Luintel and Paudyal (2006), Bampinas and Panagiotidis (2016), and Salisu et al. (2020a) argue that it's essential to take these details into account when modelling with stock data. Stock prices at the firm, industry, sector, or state level may respond differently to common economic factors such as inflation, interest rates, exchange rates, oil prices, and others[1] and ignoring such details by using the aggregate stock index data may lead to wrong conclusions.[2] To the best of our knowledge, this is the first paper to examine not only the state-level dynamics of stock returns amid a low interest rate but also from the perspective of conventional and unconventional measures of shadow rates. Our motivation for considering stock markets at the level of individual states rather than the national (aggregate) stock market index stems from the view that the core business activities of firms often occur close to their headquarters (see Pirinsky & Wang, 2006; Cheney et al., 2012). In addition, equity prices in a federating economy like the U.S. should, according to Bonato et al. (2022), have a tangible regional component to the point where investors overweight local firms in their portfolios (Korniotis & Kumar, 2013).

Thirdly, one of the key features of the non-ZLB shadow rate developed by De Rezende and Ristiniemi (2023) is the assertion that it functions as a measure of the overall stance of the monetary system and is applicable at any point in time. To test the validity or otherwise of this position, we evaluate the relationship across tranquil and turbulent periods. Notable episodes of distinct crises that have been validated to influence the performance of stock markets include the period of GFC, the popup of the Dot-com bubble, and the period of the COVID-19 outbreak.[3] The aggregation of these crises' periods formed a subsample named "turbulent period [TUP]" in this study. More so, we extend the analysis of the possible episodic nature of the relationship by examining whether the stock returns and shadow rate nexus can be generalised across the period of conventional monetary policy, which is

[1] Different sectors of the economy may respond differently to specific shocks. For example, stocks in the energy sector may react differently to oil price changes than to other types of shocks. Similarly, financial sector-based stocks may respond differently to interest rate fluctuations compared to non-financial sector stocks. In the same vein, stocks related to agriculture-based states may respond differently to weather changes relative to non-agriculture stocks.

[2] Salisu et al. (2020a), for example, demonstrate that the lack of hedging potential of the US stock market can be upturned if the price level data for the individual constituents of US stock returns is used rather than the index level data and they find the outcome to be robust to alternative methods of analyses, data frequencies and measures of inflation.

[3] There is increasing evidence supporting the episodic nature involving the global financial crisis, the COVID-19 pandemic as well as the Russia-Ukraine war in the response of stock returns to economic fundamentals such as exchange rate (see Iyke & Ho, 2021; Salisu et al., 2022), inflation (see Salisu et al., 2020b), oil price (see Swaray & Salisu, 2018; Salisu et al., 2020c; Zhang et al., 2021; Bagchi & Paul, 2023), among others.

Table 2
Panel Unit Root Test Results.

	Stock Returns	*FFR*	*CSR*	*USR*	*EXR*	*INFL*
Null Hypothesis: unit root with common process						
LLC	-5.1e+ 02[b]	-5.0e+ 02[a]	-49.9427[b]	-35.8416[b]	-5.4e+ 02[b]	-84.6302[b]
Breitung test	-3.6e+ 02[b]	-4.3e+ 02[a]	-4.9e+ 02[b]	-3.8994[a]	-4.7e+ 02[b]	-3.9e+ 02[b]
H-T test	-0.0383[b]	0.0002[a]	-4.8307[a]	-3.1e+ 02[b]	-0.2058[b]	-63.6442[b]
Null Hypothesis: unit root with individual unit root process						
IPS-MW	-5.1e+ 02[b]	-5.0e+ 02[a]	-12.6628[b]	-58.5637b	-5.4e+ 02[b]	-10.9297[b]
Null Hypothesis: no unit root with common unit root process						
Hadri Z-stat.	0.8656[b]	-7.9025[b]	21.7620[a]	33.9202[b]	-6.1420[b]	1.6e+ 03[a]

Note: The FFR is the Federal Fund Rate, CSR is the conventional shadow rate, USR is the unconventional shadow rate, EXR is the dollar exchange rate, where the Euro is the reference currency, and INFL is inflation. The stock prices, exchange rates and inflation are expressed in natural logs. The first category of panel unit root test considered includes Levin, Lin and Chu (LLC, 2002), Breitung (2000) and Harris and Tzavalis (H-T, 1999). The second category of unit root tests involving Im, Pesaran and Shin (IPS, 1997) and Maddala and Wu (MW, 1999) assumes individual unit root process as the null. The third category of unit root tests (i.e., Hadri, 2000 Lagrange Multiplier test) involves the null hypothesis of no unit root with a common unit root process in the panels. The terms *a & b* denote stationarity at the level and the first difference, respectively.

Table 3
Panel cointegration testing results.

Samples	**Without additional control**			**With additional control**		
	FFR	**CCR**	**USR**	**FFR**	**CCR**	**USR**
Full Sample	-0.0091***	-0.0081***	-0.0117***	-0.0095***	-0.0114***	-0.0305***
	(0.0006)	(0.0005)	(0.0007)	(0.0006)	(0.0008)	(0.0020)
Turbulent Periods [TUP]						
TUP	-0.0813***	-0.0668***	-0.0796***	-0.0373***	-0.0445***	-0.0505***
	(0.0046)	(0.0038)	(0.0045)	(0.0018)	(0.0037)	(0.0036)
Tranquil Periods						
Full Less TUP	-0.006***	-0.0056***	-0.0063***	-0.0344***	-0.0351***	-0.0243***
	(0.0005)	(0.0005)	(0.0005)	(0.0026)	(0.0028)	(0.0021)
Periods of Conventional and Unconventional Monetary Policies						
CMP	-0.0067***	-0.0067***	-0.0095***	-0.0192***	-0.0485***	-0.0400***
	(0.001)	(0.0012)	(0.0010)	(0.0018)	(0.0044)	(0.0032)
UCMP	-0.080***	-0.0896***	-0.0912***	-0.0855***	-0.1030***	-0.0303***
	(0.00405)	(0.0059)	(0.0044)	(0.0033)	(0.0059)	(0.0027)

Note: Standard errors in parentheses;
*p < 0.1. The cointegration test coefficient is derived from the coefficient of the error correction in the Panel ARDL model.
* *p < 0.05,
*** p < 0.01,

the period preceding the practice of quantitative easing (QE), and the period following the QE, defined as the period of unconventional monetary policy.

However, in addition to the increasing evidence of a significant connection between monetary policy and equity prices (see Gürkaynak et al., 2022), quite a number of fundamentals have also been identified as the channels through which the QE impacts the financial markets (see Joyce et al., 2010, 2012; Gern et al., 2015). Thus, since the shadow rate determines how stimulative a QE is on economic activity, it is only reasonable to be aware of the transmission channels through which the QE impacts economic activity. The exchange rate has been prominent in the literature as one of the transmission channels through which the QE affects the financial market. For instance, QE activities such as large-scale asset purchases tend to make domestic assets cheaper by substituting assets abroad due to the depreciated currency, which makes domestic consumers find foreign goods and services expensive. This, among other things, spurs our motivation to control the exchange rate in stock returns and the shadow rate nexus. Also, irrespective of whether a monetary policy is conventional or unconventional, the goal is usually to ensure the stability of the macroeconomic environment, with stable inflation being the main yardstick. In that same sense, the performance of a stock market may be sensitive to the stability (instability) of the macroeconomic environment. Given this, we further expand the measure of our control variable to include the indicator of macroeconomic stability (instability), for instance, inflation.

In terms of methodology, we employ the nonstationary heterogeneous panel data technique, which involves estimating a Panel Autoregressive Distributed Lag model that produces both the long- and short-run estimates for the examined connection. This technique is particularly suitable for panel data with large cross-sections (N) and periods (T) and given the coverage of our sampled units of fifty (50) US states with daily observations spanning February 1994 to April 2023, our choice of the nonstationary heterogeneous panel data technique is justified. Note that the nonstationary term in the technique nomenclature is derived from the fact that with increasing time observations inherent in large N and large T dynamic panels, nonstationarity is usually a concern. Therefore, as part of our preliminary analyses, we need to establish that while nonstationarity is expected, there is no evidence of an order of integration higher than one (i.e., the maximum order of integration is one). Similarly, the heterogenous term enables us to account for any inherent heterogeneity across the US states since the homogeneity assumption may be too restrictive for state-level stock markets where their peculiar economic conditions can influence the demand for stocks in respective states.

Overall, we show results that give credence to the effectiveness of FFR at stimulating stock returns in the long run, especially during crisis periods such as GFC and COVID-19. We also show that both conventional and unconventional shadow rates share a common feature, as they uniformly show how downward-sticky the stock markets can be in the long run with a rising shadow rate in virtually all 50 states in the U.S. Our findings offer robust insights into the usefulness of unconventional monetary policy measures for stock market performance during crises and normal periods. Our findings have some implications for policymakers and investors, particularly those in the US stock market.

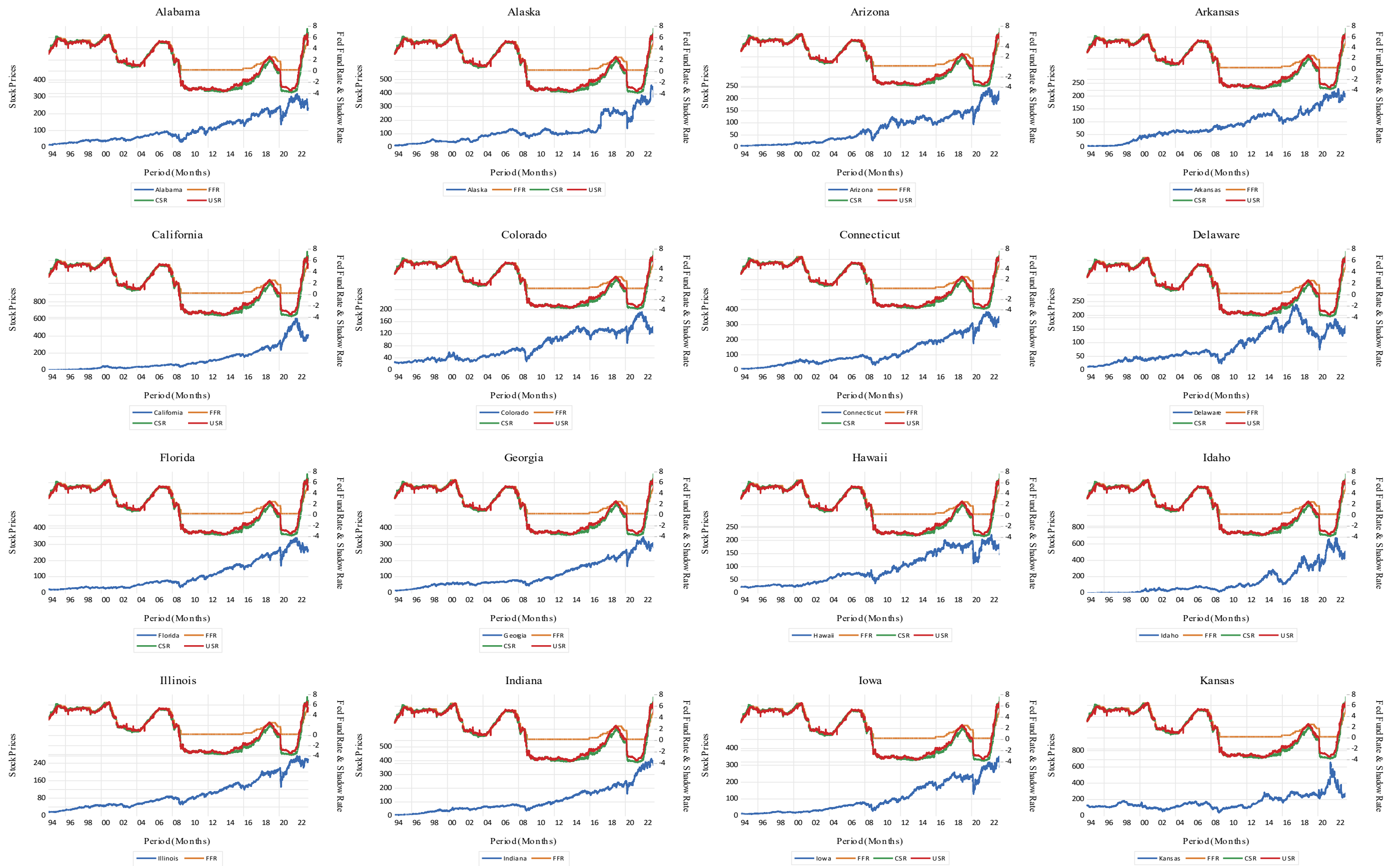

Fig. 1. Trends instock prices of US 50 states relative to daily federal funds rate (FFR) and shadow rates.

The rest of the paper is organized in the following order: Section 2 describes the data and offers some preliminary results; Section 3 details the technique employed; and Section 4 presents and discusses the results. We conclude the paper in Section 5.

2. Data and preliminary results

From February 1994 to April 2023, the daily state-level stock price index of the 50 U.S. states from which we compute stock returns was obtained from Bonoto et al. (2022). For the shadow rate variables, the shadow rate of Wu and Xia (2016, 2020) obtained from https://www.atlantafed.org/cqer/research/wu-xia-shadow-federal-funds-rate is the proxy for conventional shadow rate (CSR), while the shadow rate of De Rezende and Ristiniemi (2023) obtained from www.rafaelbderezende.com represent the unconventional shadow rate (USR). Unlike the Wu and Xia approach, the De Rezende and Ristiniemi (2023) shadow rate is estimated using two-factor ($p = 2$) and three-factor ($p = 3$) term structure models. To this end, the unconventional shadow rates (USR) in the context of this study are measured as the average of both the two- and three-factor shadow rates of De Rezende and Ristiniemi (2023). The Federal Fund Rate (FFR) data were obtained from the same source from which we retrieved the USR. Regarding the control variables, both the exchange rate (EXR), where the Euro is the reference currency, and inflation (INFL), measured as the log of the consumer price index, were sourced from the FED data (https://fred.stlouisfed.org).

Table 1 presents the summary statistics of the variables across the different episodes of interest. A glance at the table shows that the average returns on stocks at the state level in the U.S. are relatively lower in turbulent periods compared to periods of tranquillity. Also, the average stock returns appear to be higher when the monetary policy is conventional compared to the period when the monetary policy is unconventional. Moving forward, the standard deviation statistic, which measures dispersion from the mean level, shows that the stock market is relatively more volatile in crisis periods. Regarding the policy variables, a look at the table shows that during a conventional policy period, the shadow rates, irrespective of whether they are conventional or unconventional, equal the FFR, which is, by default, a measure of the monetary policy stance. As expected, however, while the shadow rates are negative during an unconventional policy period, the mean statistic remains positive in the case of the FFR. This, in particular, conforms with the intuition of the zero lower bound (ZLB) feature of the standard monetary policy rate, prompting central banks to turn to unconventional monetary actions.

Given the large time-series dimension of the variables, we further subject each of the variables of interest to unit root testing, which is required when working with macro-panels with large N and large T. Rather than assuming the presence of a unit root at random, we take an evidence-based approach by applying three different forms of panel unit root tests. We show that the variables' stationarity status primarily revolves around the I(0) and I(1) order of integration, and this evidence holds for all the various types of unit root tests considered. Further, we test for any possible cointegration in the model based on the error correction term of the competing estimators mean group (MG) and pooled mean group (PMG) used in this study. Given the error correction representation of Eq. (2), the null hypothesis of the cointegration test is that there is no cointegration, while the alternative is that at least one unit is cointegrated. Regardless of which competing estimators are considered, a non-rejection of the null hypothesis in both cases simply suggests no cointegration. The cointegration results are presented in Table 3, where we find the presence of cointegration for the connection

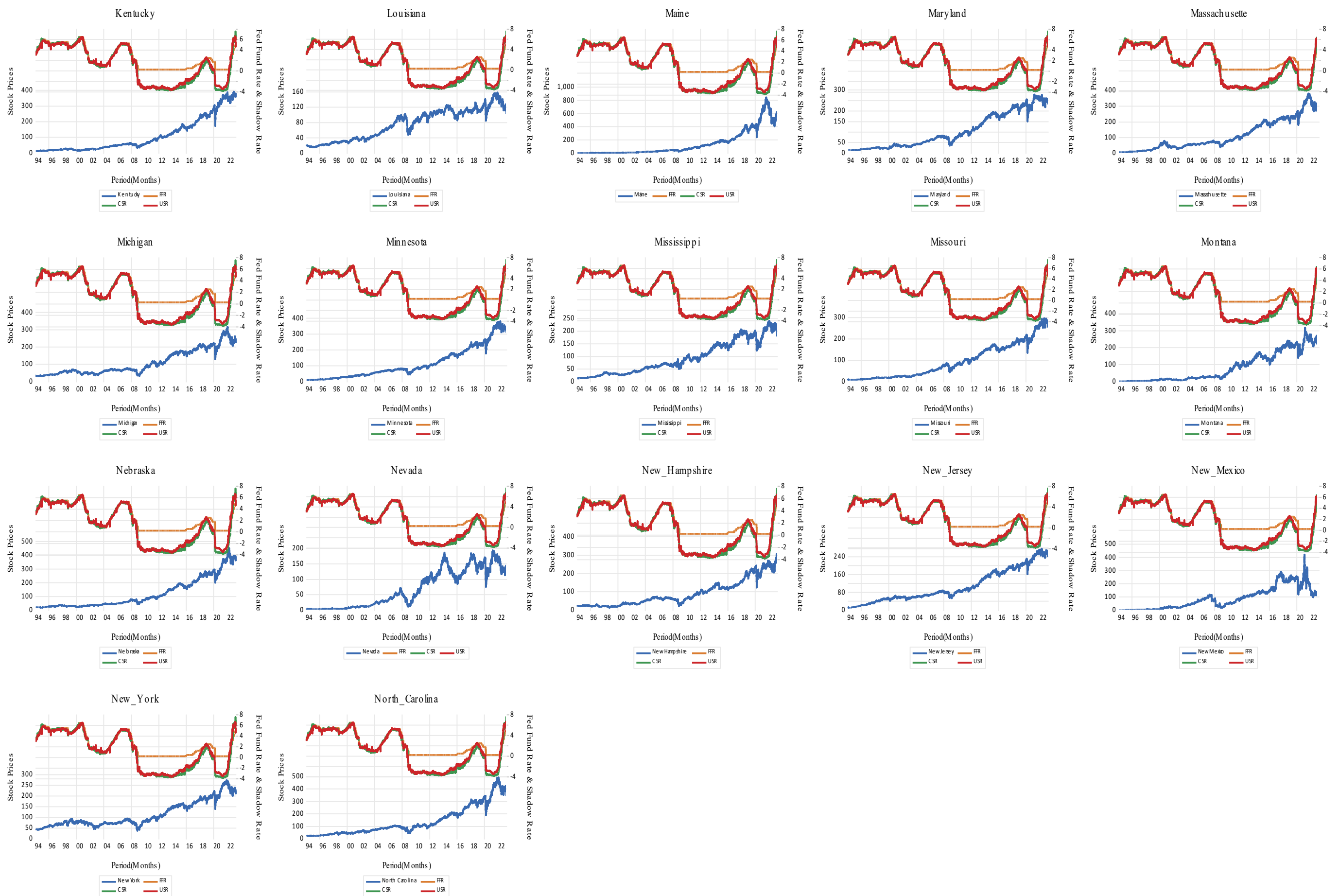

Fig. 1. (*continued*).

between stock returns and each of the monetary policy variables under consideration. In other words, all the coefficients are negative and statistically significant, as expected for cointegration to exist between the dependent and the independent variables.

Both unit root and the cointegration testing have provided the background for further analyses in determining the long-run and short-run relationships between stock returns and the various conventional and unconventional monetary policy instruments and the speed of adjustment when the system is confronted with a shock. We also complement the preliminary analysis with a visual representation of the variables' likely co-movements (see Fig. 1). In the figure, the FFR appears to be trending at the fixed value of zero during the crisis periods. The figure also depicts the shadow rates trending in the opposite direction from the stock markets, which is very much in line with economic theory. However, while the figure suggests little or no difference between the variants of the shadow rates under consideration, it is still not a sufficient condition to draw a conclusion on the hypothesis that they impact stock markets differently.

3. Methodology

Given that the variables of interest have the features of large cross-sectional (N) and large time-series (T) dimensions, the non-stationary heterogeneous panel data model is considered the most appropriate in this study. Thus, Eq. (1) is the generic representation of our ARDL panel data model, which enables us to capture the heterogeneity dynamics of the stock markets of the investigated 50 U.S. states. Our preference for the panel ARDL model is also motivated by its suitability for modelling variables of different orders of cointegration in a single framework.

$$s_{it} = \sum_{j=1}^{p} \beta_{ij} s_{i,t-j} + \sum_{j=0}^{q} \delta'_{ij} X_{i,t-j} + \mu_i + \varepsilon_{it} \tag{1}$$

where s_{it} is the log of stock prices, X_{it} is a $k \times 1$ vector of the explanatory variables, δ_{ij} is a $k \times 1$vector of coefficients, β_{ij} are scalars while μ_i is the state-specific effect. On this note, Eq. (1) can be further reparametrized into the error correction equation to capture simultaneously the short-run dynamics as well as the deviation from the equilibrium state.

$$\Delta s_{it} = \sum_{j=1}^{p-1} \beta^*_{ij} s_{i,t-j} + \sum_{j=0}^{q-1} \delta^{*\prime}_{ij} \Delta X_{i,t-j} + \gamma_i \left(s_{i,t-1} - \lambda'_i X_{it}\right) + \mu_i + \varepsilon_{it} \tag{2}$$

The term $\gamma_i = -\left(1 - \sum_{j=1}^{p} \beta_{ij}\right)$ is the error correction parameter denoting the potential of long-run equilibrium in the relationship; $\lambda_i = \sum_{j=0}^{q} \delta_{ij} / \left(1 - \sum_k \beta_{ik}\right)$ is the long-run estimates; and $\beta^*_{ij} = -\sum_{r=j+1}^{p} \beta_{ir}$ $(j = 1, \ldots, p-1)$; and $\delta^*_{ij} = -\sum_{r=j+1}^{q} \delta_{ir}$ $(j = 1, \ldots, q-1)$ are the short-run estimates.

Note that the explanatory variables comprising the CSR, USR and FFR are distinctly included in the regression model under two alternative scenarios, such as the models with and without control variables (exchange rates and inflation). Also, for the purpose of estimation, only the first lag is accommodated for all the variables in the short run as the determination of a common optimal lag within the panel framework is not feasible. In line with theory, we hypothesize a negative relationship between the FFR and stock returns as higher interest rates tend to negatively affect the earnings of firms, which, by extension, puts

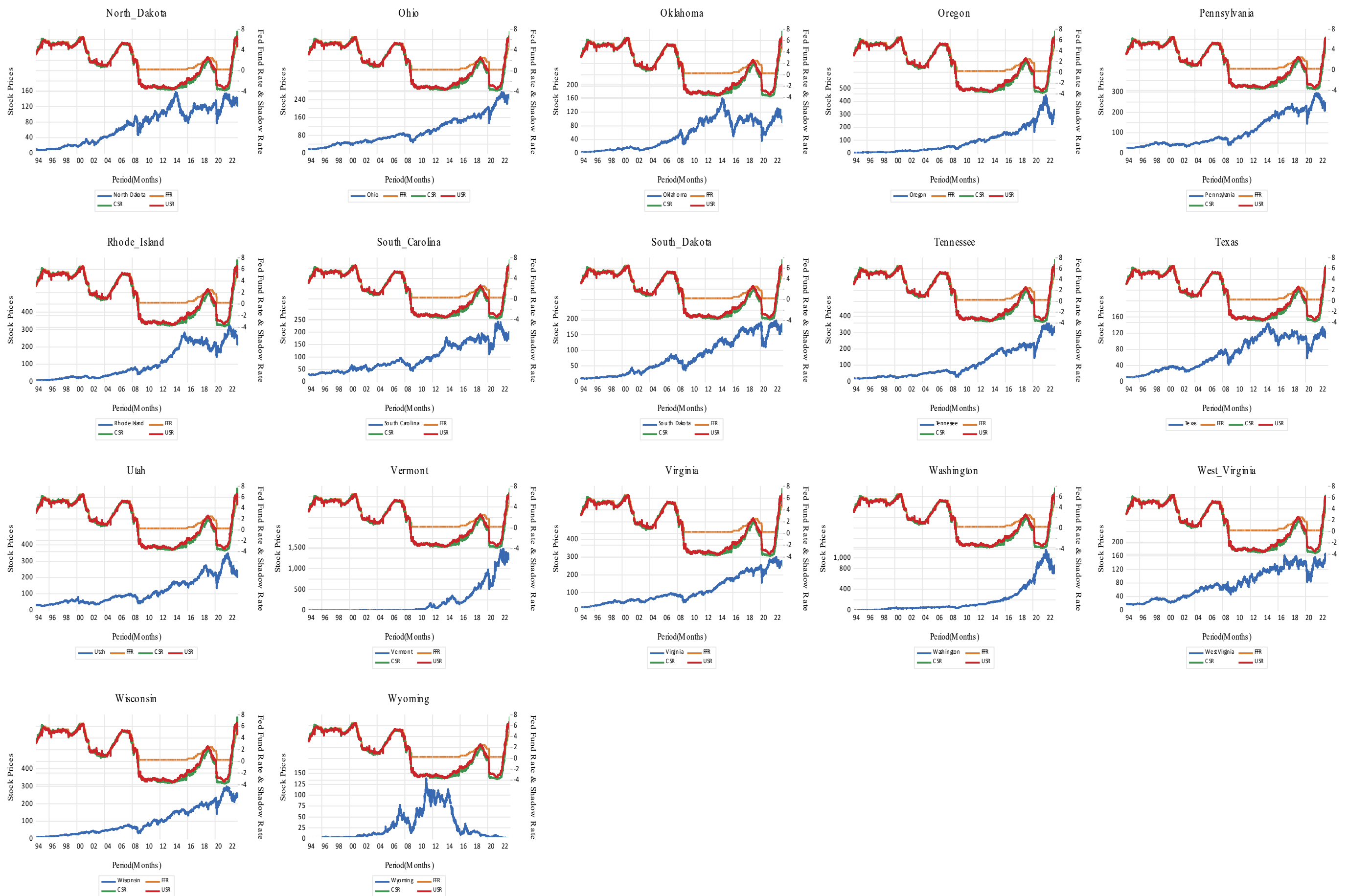

Fig. 1. (*continued*).

pressure on their share prices, thus lowering future returns. However, the connection between shadow rate and stock returns is not clear-cut. Several views, such as the mainstream view, debasement view, expansionary view, and interest rate view,[4] have been adduced in the literature to explain this connection, particularly from the perspective of quantitative easing, which is a common unconventional monetary policy often adopted by the Federal Reserve Bank in the US. We focus on the interest rate view regarding quantitative easing (QE) given the subject of this paper which is shadow rates. This view assumes that QE causes a drop in real interest rates, leading to an increase in demand, employment, and stock markets. However, the critical factor for the boom phase is the drop in interest rates. If QE does not result in a real interest rate drop in the short run, it will not cause an economic boom at this stage. In other words, the relationship between shadow rates and the US stock markets may differ between the long run and short run.

In terms of estimation, we adopt the two prominent methods for Panel ARDL analyses, namely the Pooled Mean Group (PMG) (see Pesaran, Shin, and Smith, 1997) and the Mean Group (MG) (see Pesaran and Smith, 1995) estimators. The difference between the two estimators lies in how long-run estimates are treated. While all the parameters, such as the intercepts, slope coefficients, and error variances, are all allowed to differ across groups in the case of the MG estimator, the PMG estimator constrains the long-run coefficients to be equal across groups while the intercept, short-run coefficients, and error variances are allowed to differ across the groups (as would the MG estimator). In order to choose between the MG and PMG estimators, the familiar Hausman test is performed, and we find the non-rejection of the null hypothesis evident in all cases considered. Hence, only the estimation results obtained via the PMG were presented and discussed.

4. Empirical results

In the quest to offer new insight into the nexus between stock returns and shadow rates, the innovation in this study is to determine whether the assumption of ZLB, which is central to the concept of shadow rate, matters in the first place. As a result, the empirical estimates presented in the following tables depict separately the response of stock returns to CSR in Table 5 and USR in Table 6, respectively. However, we begin our empirical analysis with the comparative effectiveness of the FFR during the conventional policy period compared to the unconventional policy period (see Table 4). The essence is to determine why preference is expected to be given to shadow rates during the unconventional policy period. On the whole, we considered the episodic dynamics of the nexus across some notable episodes that define periods of crisis and tranquillity in the financial markets, both in the model with control variables and the model without control variables.

4.1. Empirical estimates on the FFR-stock returns nexus

Regardless of whether the estimated model is with or without control variables, we find the coefficients on the error correction (EC) in Table 4 to be correctly signed and statistically significant in all alternative scenarios considered. We find the short-run effect of the FFR on stock returns to be positive in crisis periods and during unconventional monetary policy periods. While the robustness of this finding is evident both in the models with and without control variables, the reverse

[4] These details are succinctly summarized in this link:https://www.managementstudyguide.com/effect-of-quantitative-easing-on-stock-markets.htm

Table 4
Shadow rate – US State-level stock returns [Using Fed Fund Rate (FFR)].

Variable	Without Control				
	Full Sample [FS]	Turbulent Periods [TUP]	FS Less TUP	CMP	UCMP
EC	-0.0091***	-0.0813***	-0.0060***	-0.0067***	-0.0800***
	(0.0006)	(0.0046)	(0.0005)	(0.0010)	(0.0040)
D.FFR	0.0356***	0.1970***	-0.0200***	-0.0210***	0.0800***
	(0.00336)	(0.0206)	(0.0034)	(0.0040)	(0.0056)
FFR	-0.277***	-0.2790***	-0.2340***	0.0194	-0.0990***
	(0.0188)	(0.0122)	(0.0265)	(0.0274)	(0.0073)
Constant	0.0536***	0.4600***	0.0401***	0.0360***	0.2820***
	(0.00310)	(0.0276)	(0.0025)	(0.0050)	(0.0171)
With Control					
EC	-0.0095***	-0.0373***	-0.0344***	-0.0192***	-0.0855***
	(0.0006)	(0.0018)	(0.00263)	(0.0018)	(0.0033)
D.FFR	0.0303***	0.0989***	-0.0425***	-0.0284***	0.1340***
	(0.0034)	(0.0088)	(0.0038)	(0.0039)	(0.0058)
FFR	-0.2510***	0.2130*	-0.0066	0.0104	-0.0402***
	(0.0416)	(0.1220)	(0.0066)	(0.0134)	(0.0067)
D.EXR	-0.110***	6.8320***	-0.0962***	0.0535***	0.0112
	(0.0148)	(0.3610)	(0.0141)	(0.0191)	(0.0142)
EXR	-1.045***	-0.2040***	-1.4870***	-1.4560***	-1.9510***
	(0.347)	(0.0256)	(0.1320)	(0.2420)	(0.1190)
D.INF	1.378***	-0.8930***	0.7930***	-0.1270	1.1360***
	(0.217)	(0.2330)	(0.2550)	(0.3660)	(0.2050)
INF	0.233	0.2900	-2.5050***	3.4290***	-8.2030***
	(0.570)	(0.3450)	(0.6910)	(0.2500)	(0.412)
Constant	0.0405***	0.1160***	0.4500***	-0.2080***	3.1460***
	(0.0023)	(0.0080)	(0.0331)	(0.0213)	(0.118)
Obs.	17,500	4950	12,500	8100	8300

Note: FS = Full Sample and covers the entire data sample; TUP = Turbulent Periods; CMP = Conventional Monetary Policy Period (prior to QE or pre-GFC); and UCMP = Unconventional Monetary Policy Period (post-QE or post-GFC). Standard errors in parentheses;

* * $p < 0.05$,

* $p < 0.1$. FFR is the Federal Fund Rate, and its coefficient denotes the long-run estimate, while D.FFR is for the short run where the 'D' is the first difference operator; EC is the error correction term. INF is measured as a log of consumer prices; EXR is measured as a log of exchange rates where the US dollar is the reference currency. The long run and short run of these control variables are estimated the same way as the shadow rates.

*** $p < 0.01$,

Table 5
Shadow rate–US State-level stock returns [Using CSR].

Variable	Without Control				
	Full Sample [FS]	Turbulent Periods [TUP]	FS Less TUP	CMP	UCMP
EC	-0.0081***	-0.0668***	-0.0056***	-0.0067***	-0.0896***
	(0.0005)	(0.0038)	(0.0005)	(0.0012)	(0.0059)
D.CSR	0.0027*	0.1160***	-0.0174***	-0.0094***	-0.0019
	(0.0016)	(0.0106)	(0.0020)	(0.0018)	(0.0027)
CSR	-0.2280***	-0.2340***	-0.1780***	0.0197	-0.0441***
	(0.0170)	(0.0133)	(0.0215)	(0.0271)	(0.0031)
Constant	0.0469***	0.3690***	0.0370***	0.0362***	0.2820***
	(0.0026)	(0.0219)	(0.0023)	(0.0045)	(0.0194)
With Control					
EC	-0.0114***	-0.0445***	-0.0351***	-0.0485***	-0.1030***
	(0.0008)	(0.0037)	(0.0028)	(0.0044)	(0.0059)
D.CSR	0.0017	-0.0034	-0.0203***	-0.0170***	0.0122***
	(0.0016)	(0.0023)	(0.0020)	(0.0021)	(0.0027)
CSR	-0.1530***	0.4880***	-0.0121**	0.0757***	-0.0288***
	(0.0223)	(0.1460)	(0.0050)	(0.0078)	(0.0031)
D.EXR	-0.1270***	6.9010***	-0.0820***	0.0738***	-0.0988***
	(0.0135)	(0.3700)	(0.0134)	(0.0189)	(0.0129)
EXR	-0.6200**	-0.0639***	-1.0440***	-0.4360***	-0.9430***
	(0.2660)	(0.0108)	(0.1060)	(0.0868)	(0.0911)
D.INF	1.5850***	0.8490***	0.7170***	0.1890	1.3740***
	(0.2180)	(0.1520)	(0.2520)	(0.3760)	(0.2130)
INF	1.3280***	2.5200***	-2.0540***	-14.0900***	-2.9310***
	(0.3550)	(0.1370)	(0.6610)	(1.9340)	(0.2200)
Constant	-0.0114***	-0.3160***	0.3970***	2.9160***	1.5320***
	(0.0016)	(0.0239)	(0.0318)	(0.2650)	(0.0819)
Obs.	17,500	4.950	12,500	8100	8300

Note: FS = Full Sample and covers the entire data sample; TUP = Turbulent Periods; CMP = Conventional Monetary Policy Period (prior-to QE or pre-GFC); and UCMP = Unconventional Monetary Policy Period (post-QE or post-GFC). Standard errors in parentheses;

* $p < 0.1$. CSR is the Conventional Shadow Rate (Wu & Xia, 2016), and its coefficient denotes the long-run estimate, while the D.CSR is for the short run where the 'D' is the first difference operator; EC is the error correction term. INF is measured as a log of consumer prices; EXR is measured as a log of exchange rates where the US dollar is the reference currency. The long run and short run of these control variables are estimated the same way as the shadow rates.

** $p < 0.05$,

*** $p < 0.01$,

appears to be the case when the economy is calm and during a period of conventional monetary policy. Notwithstanding the widespread assertion that monetary policy is neutral in the long run, our long-run estimates are more in tune with the traditional hypothesis of a negative relationship between monetary policy and stock returns. For instance, we show results suggesting that a higher FFR negatively affects firms' earnings in the long run, irrespective of whether the estimated model is with or without control variables. This, in particular, conforms to the intuition that a high interest rate will likely encourage waiting and reduce investment (see Aramonte et al., 2019; Dotsis, 2020). Indeed, our finding of the long-run effect of FFR on stock returns supports the school of thought that argues for the non-neutrality of money monetary policy in the long run (see Kam et al., 2019). In their investigation of the real long-run effects of the structural stance of monetary policy, Gil and Iglesias (2019), for example, rely on models with endogenous growth to show that monetary stimulus can encourage investment and, by extension, lead to a boom in economic activity in the stock markets (see also Hori, 2019).

Equally, an interesting result in Table 4 is that we find both the short-run and long-run impacts of the FFR on stock returns mostly positive during unconventional monetary policy and in crisis periods. This not only contradicts the hypothesis of an inverse relationship between stock markets and interest rates but also fuels doubt that the shadow rate equals the short-term interest rate, in this case, FFR, during the period of conventional monetary policy. For instance, while the assumption of FFR's equality to shadow rates might seem viable when the shadow rate is based on ZLB, it might be erroneous to assume the same for a non-ZLB shadow rate that measures the overall stance of monetary policy in any policy environment. Thus, the following is a comparative analysis of stock returns' response to the ZLB-based shadow rate (CSR) compared to

Table 6
Shadow rate–US State-level stock returns [Using USR].

Variable	Without Control				
	Full Sample [FS]	Turbulent Periods [TUP]	FS Less TUP	CMP	UCMP
EC	-0.0117*** (0.0007)	-0.0796*** (0.0045)	-0.0063*** (0.0005)	-0.0095*** (0.0010)	-0.0912*** (0.0044)
D.USR	0.0382*** (0.0020)	0.1690*** (0.0105)	0.0017 (0.0028)	0.0435*** (0.0031)	0.0346*** (0.0026)
USR	-0.1970*** (0.0093)	-0.1730*** (0.0075)	-0.1450*** (0.0155)	0.1080*** (0.0334)	-0.0396*** (0.0026)
Constant	0.0606*** (0.0030)	0.4090*** (0.0245)	0.0376*** (0.0024)	0.0396*** (0.0038)	0.4020*** (0.0180)
With Control					
EC	-0.0305*** (0.0020)	-0.0505*** (0.0036)	-0.0243*** (0.0021)	-0.0400*** (0.0032)	-0.0303*** (0.0027)
D.USR	0.0382*** (0.0019)	0.0423*** (0.0027)	-0.0046* (0.0027)	0.0334*** (0.0031)	0.0327*** (0.0026)
USR	-0.1350*** (0.0135)	0.3020** (0.1420)	-0.0721*** (0.0130)	-0.0905*** (0.0204)	-0.1860*** (0.0172)
D.EXR	1.1740*** (0.2180)	6.6320*** (0.3720)	0.5620** (0.2440)	1.7800*** (0.3440)	0.7360*** (0.1820)
EXR	-0.0423*** (0.0056)	-0.0842*** (0.0078)	-0.0173*** (0.0057)	0.1360*** (0.0119)	-0.0464*** (0.0087)
D.INF	-0.8800*** (0.1110)	-0.0376 (0.1350)	-1.3310*** (0.1650)	-0.2240** (0.1080)	-0.7650*** (0.2460)
INF	-9.2150*** (0.7120)	1.6540*** (0.1500)	-4.2880*** (0.8660)	-24.6400*** (2.5650)	0.7680** (0.3330)
Constant	1.2630*** (0.0858)	-0.1630*** (0.0096)	0.5040*** (0.0427)	4.136*** (0.331)	0.0421*** (0.0020)
Obs.	17,500	4950	11,950	8900	8500

Note: FS = Full Sample and covers the entire data sample; TUP = Turbulent Periods; CMP = Conventional Monetary Policy Period (prior-to QE or pre-GFC); and UCMP = Unconventional Monetary Policy Period (post-QE or post-GFC). Standard errors in parentheses;

* $p < 0.1$. USR is the unconventional Shadow Rate of De Rezende and Ristiniemi (2022), and its coefficient denotes the long-run estimate, while the D.CSR is for the short run where the 'D' is the first difference operator; EC is the error correction term. INF is measured as a log of consumer prices; EXR is measured as a log of exchange rates where the US dollar is the reference currency. The long run and short run of these control variables are estimated the same way as the shadow rates.

** $p < 0.05$,

*** $p < 0.01$,

the non-ZLB-based shadow rate (USR).

4.2. Empirical estimate on the shadow rates -stock returns nexus: CSR or USR?

Here, the goal is to determine the extent to which stock returns respond differently to the variant of shadow rates based on ZLB compared to the variant that does not impose any lower bound constraint on nominal interest rates. The former, which is based on Wu and Xia (2016, 2020), is defined as conventional shadow rates (CSR) in this study, while the latter, which defines our unconventional shadow rate (USR), is based on De Rezende and Ristiniemi (2022). Thus, presented in Table 5 are empirical estimates of the response of stock returns to CSR, while Table 6 houses the empirical estimates of the responses of stock returns to USR. We show that the coefficients on the error correction (EC) are correctly signed and statistically significant irrespective of whether shadow rate CSR or USR and IT doesn't matter whether the sample is fully utilised or partially utilised to distinguish between the periods of turbulence and tranquillity. However, the speed of adjustment with which shocks to the dynamic of stock returns are revertible is higher in the models with control variables, particularly during the crisis periods. More importantly, the fact that the stock return responds positively to both conventional and unconventional shadow rates during turbulent periods, particularly in the short run, conforms to our earlier finding that stock returns also respond positively to FFR. What this portends is that even when the lowering of the FFR is limited during the crisis periods, its effectiveness at stimulating the stock market by lowering the short-term interest rates is as effective as that of the shadow rates, at least in short-run situations.

The aforementioned notwithstanding, we find stock returns reacting negatively to conventional shadow rates (CSR) in the short-run situation, both in a period of tranquilly and in a period of conventional monetary policy. This is theoretically reasonable, particularly in the context of the Wu and Xia (2016, 2020) shadow rate, which is equal to the short-term interest rates (i.e., FFR) in the period of conventional monetary policy, where a higher interest rate is posited to impact the stock market negatively. However, the effect is both positive and statistically significant during unconventional monetary policy, particularly in the model that includes exchange rate and inflation as control variables. While this might contradict some of the existing findings where the effects of monetary policy on stock prices are reported as negative (see, for example, Gürkaynak et al., 2019; Swanson, 2021; Gürkaynak, Karasoy-Can and Seok Lee, 2022, among others), it is theoretically reasonable given that the shadow rate denotes the expansion of the Federal Reserve's balance sheet over the zero lower bound (ZLB) by dropping into negative territory. Even when the lower bound constraints are not applicable, the shadow rate in that respect still proves significant for stimulating the stock market, at least in the short-run, irrespective of whether it is in the period of unconventional monetary policy or conventional monetary policy. This, in particular, confirms an important feature of the shadow rates developed by De Rezende and Ristiniemi (2022), which measure the interest rate of unconventional monetary policy at any point in time prior to and during the lower bound period.

From the long-run perspective, however, we find the coefficients on both the CRS and USR to be negative not only when the sample is fully utilized but also during the crisis periods. It is instructive at this juncture to recall that the shadow rate corresponds to the unobserved short-term interest rate consistent with longer-term rates that would have prevailed had the interest rate lower bound not been biding. Based on the current analysis, it can be concluded that while the shadow rate is anticipated to align with the long-term rate, its capacity to boost the economy during a crisis appears to be effective only in the short term. In the long-run, the shadow rate even when not bidding by the lower bound constraint tends to impact the stock market negatively even in the crisis period. The only exception in this regard is when the period of conventional monetary policy and exchange rate and inflation are included in the model. To put it differently, the outcome appears to suggest that the intended boom effect of unconventional expansionary monetary policy measures[5] In stimulating activities in the stock market only becomes evident in the short run.

In spite of their differences, both conventional and the unconventional shadow rates tends to share a common feature. They reveal how the stock markets tend to be downward-sticky in the long run when there is a rising shadow rate. Policymakers often use unconventional

[5] Please note that an increase in the shadow rate would indicate a contractionary unconventional monetary policy measure, while a decrease in the rate would suggest an expansionary unconventional monetary policy measure.

Table 7
Shadow rate – US State-level stock returns [Using USR with Full Sample].

Variables	Alabama	Alaska	Arizona	Arkansas	California	Colorado	Connecticut	Delaware	Florida	Georgia	Hawaii	Idaho	Illinois
ec	-0.0197***	-0.0096**	-0.0111***	-0.0046	-0.0092***	-0.0259***	-0.0117***	-0.0272***	-0.0133***	-0.0117***	-0.0196***	-0.0142***	-0.0095***
	(0.0048)	(0.0044)	(0.0043)	(0.0032)	(0.0030)	(0.0069)	(0.0036)	(0.0056)	(0.0038)	(0.0034)	(0.0047)	(0.0047)	(0.0033)
D.USR1	0.0462***	0.0323***	0.0391***	-0.0031	0.0289***	0.0394***	0.0386***	0.0380***	0.0392***	0.0259***	0.0392***	0.0471**	0.0347***
	(0.0098)	(0.0099)	(0.0104)	(0.0082)	(0.0100)	(0.0103)	(0.0091)	(0.0105)	(0.0082)	(0.0070)	(0.0085)	(0.0208)	(0.0063)
USR1	-.1823***	-0.1094	-0.2366***	0.1225	-0.2363***	-0.1637***	-0.1713***	-0.1831***	-0.2575***	-0.1542***	-0.2018***	-0.2740**	-0.1335**
	(0.04197)	(0.0857)	(0.0771)	(0.2699)	(0.0889)	(0.0340)	(0.0644)	(0.0325)	(0.0576)	(0.0491)	(0.0384)	(0.1215)	(0.0542)
Constant	0.0982***	0.0533***	0.0552***	0.0286**	0.0535***	0.1178***	0.0636***	0.1269***	0.0685***	0.0624***	0.0928***	0.0782***	0.0504***
	(0.0222)	(0.0204)	(0.0178)	(0.0138)	(0.0136)	(0.0301)	(0.0168)	(0.0246)	(0.0172)	(0.0157)	(0.0211)	(0.0210)	(0.0152)
	Indiana	**Iowa**	**Kansas**	**Kentucky**	**Louisiana**	**Maine**	**Maryland**	**Massachusetts**	**Michigan**	**Minnesota**	**Mississippi**	**Missouri**	**Montana**
ec	-0.0099***	-0.0247***	-0.0071**	-0.0135***	-0.0143***	-0.0091**	-0.0110***	-0.0113***	-0.0177***	-0.0091***	-0.0180***	-0.0068**	-0.0151***
	(0.0032)	(0.0086)	(0.0033)	(0.0052)	(0.0037)	(0.0036)	(0.0038)	(0.0036)	(0.0052)	(0.0027)	(0.0041)	(0.0029)	(0.0044)
D.USR1	0.0319***	0.0384***	0.0289***	0.0285***	0.0587***	0.0316*	0.0442***	0.0375***	0.0359***	0.0260***	0.0328***	0.0333***	0.0356**
	(0.0085)	(0.0128)	(0.0086)	(0.0079)	(0.0095)	(0.0170)	(0.0087)	(0.0098)	(0.0089)	(0.0067)	(0.0081)	(0.0072)	(0.0153)
USR1	-0.1571**	-0.1432***	-0.3526***	-0.1347***	-0.2831***	-0.2922*	-0.2184***	-0.1941***	-0.1980***	-0.2329***	-0.1946***	-0.2300***	-0.3581***
	(0.0707)	(0.0548)	(0.1244)	(0.0484)	(0.0584)	(0.1594)	(0.0663)	(0.0713)	(0.0476)	(0.0622)	(0.0374)	(0.0867)	(0.0839)
Constant	0.0553***	0.1292***	0.0415***	0.0623***	0.0730***	0.0557***	0.0572***	0.0612***	0.0885***	0.0509***	0.0876***	0.0385***	0.0722***
	(0.0147)	(0.0438)	(0.0146)	(0.0223)	(0.0165)	(0.0155)	(0.0173)	(0.0162)	(0.0239)	(0.0124)	(0.0184)	(0.0126)	(0.0176)
	Nebraska	**Nevada**	**New Hampshire**	**New Jersey**	**New Mexico**	**New York**	**North Carolina**	**North Dakota**	**Ohio**	**Oklahoma**	**Oregon**	**Pennsylvania**	**Rhode Island**
ec	-0.0051	-0.0140***	-0.0119**	-0.0108***	-0.0150***	-0.0170***	-0.0139***	-0.0098**	-0.0100***	-0.0181***	-0.0066**	-0.0129***	-0.0133***
	(0.0032)	(0.0047)	(0.0052)	(0.0031)	(0.0047)	(0.0057)	(0.0043)	(0.0046)	(0.0035)	(0.0048)	(0.0034)	(0.0039)	(0.0035)
D.USR1	0.0197***	0.0561***	0.0590***	0.0227***	0.0654***	0.0348***	0.0415***	0.0284***	0.0273***	0.0707***	0.0309***	0.0336***	0.0362***
	(0.0074)	(0.0147)	(0.0110)	(0.0063)	(0.0194)	(0.0080)	(0.0095)	(0.0094)	(0.0063)	(0.0122)	(0.0104)	(0.0074)	(0.0093)
USR1	-0.3367**	-0.3535***	-0.2317***	-0.1071**	-0.1423	-0.1358***	-0.2332***	-0.1220	-0.1448***	-0.2316***	-0.2554**	-0.2186***	-0.2804***
	(0.1576)	(0.0889)	(0.0839)	(0.0491)	(0.1177)	(0.0437)	(0.0620)	(0.0852)	(0.0520)	(0.0559)	(0.1299)	(0.0535)	(0.0603)
Constant	0.0324***	0.0639	0.0600***	0.0572***	0.0729***	0.0850***	0.0747***	0.0471**	0.0530***	0.0771***	0.0389***	0.0660***	0.0680***
	(0.0148)	(0.0184)	(0.0228)	(0.0145)	(0.0196)	(0.0268)	(0.0206)	(0.0196)	(0.0159)	(0.0186)	(0.0142)	(0.0178)	(0.0158)
	South Carolina	**South Dakota**	**Tennessee**	**Texas**	**Utah**	**Vermont**	**Virginia**	**Washington**	**West Virginia**	**Wisconsin**	**Wyoming**		
ec	-0.0187***	-0.0104***	-0.0130***	-0.0160***	-0.0199***	-0.0039	-0.0119***	-0.0080***	-0.0191***	-0.0116***	-0.0005		
	(0.0057)	(0.0039)	(0.0039)	(0.0044)	(0.0052)	(0.0028)	(0.0036)	(0.0026)	(0.0053)	(0.0037)	(0.0068)		
D.USR1	0.0340***	0.0386***	0.0345***	0.0443***	0.0503***	0.0231	0.0332***	0.0204**	0.0360***	0.0327***	-0.0140		
	(0.0089)	(0.0088)	(0.0087)	(0.0077)	(0.0098)	(0.0163)	(0.0072)	(0.0102)	(0.0088)	(0.0085)	(0.0240)		
USR1	-0.1578***	-0.1795***	-0.2938***	-0.1395***	-0.1921	-1.2243**	-0.1630***	-0.2067*	-0.1621***	-0.2117***	4.1286		
	(0.0411)	(0.0694)	(0.0666)	(0.0398)	(0.0450)	(0.6347)	(0.0502)	(0.1066)	(0.0386)	(0.0609)	(54.4882)		
Constant	0.0906***	0.0517***	0.0676	0.0728	0.0991	0.0364***	0.0628***	0.0534***	0.0881***	0.0600***	-0.0016		
	(0.0260)	(0.0168)	(0.0178)	(0.0186)	(0.0243)	(0.0114)	(0.0165)	(0.0122)	(0.0230)	(0.0164)	(0.0200)		

Note: Standard errors in parentheses;
[*] $p < 0.1$. USR is the Unconventional Shadow Rate [Shadow Rate of De Rezende and Ristiniemi (2023) and its coefficient denotes the long-run estimate, while the D.USR is for the short run where the 'D' is the first difference operator; ec is the error correction term.
[**] $p < 0.05$,
[***] $p < 0.01$,

monetary policy measures when the policy rate appears to have reached its limit. However, their effectiveness in stimulating economic activity may only be viable in the short run. On the other hand, in the long run, the reverse may be true. However, even when it is impossible to lower the FFR beyond the zero bounds, it proves effective at stimulating stock returns in the long run during crisis periods.

4.3. Robustness check

Given the federating characteristics of the U.S. economy, this study uses the state-level stock market to accommodate the probable existence of any inherent differences in the stock market behaviour of the investigated economy at the state level. Although the estimation technique employed can accommodate the probability of such heterogeneity, for the sake of robustness, we employ a more rigorous approach to generate individual results for each of the 50 states in the U.S. Having shown that there is little or no significant difference in the response of stock returns to the variants of shadow rates both in terms of the direction and significance of the response, the individual state results presented in Table 7 based on De Rezende and Ristiniemi's (2022) shadow rate (i.e., USR). Starting with the coefficients on the error correction (EC) term, while it is correctly signed in all 50 states, we find a few instances where the coefficients are not statistically significant, such as in Nebraska, Vermont, and Wyoming.

With respect to the short-run and long-run dynamics of the nexus, the results are very robust to what was earlier reported when the probability of heterogeneity was captured inherently within the estimator. For example, we find the short-run coefficients on the shadow rate to be positive and statistically significant in about 47 states. On the other hand, we find long-run coefficients on the shadow rates to be negative in about 47 states. Even in the few isolated cases, such as in the cases of Arkansas and Wyoming, where the result seems otherwise, it is still not statistically significant. In sum, irrespective of the peculiarities of stock markets in each individual U.S. state, the potential of shadow rate to stimulate economic activity in the stock market is only viable in the short run and largely otherwise in the long run.

5. Conclusions

In this paper, we examine the nexus between shadow (conventional and unconventional) rates and US State-level stock returns using a panel ARDL technique suitable for the estimation of both short- and long-run effects of shadow rates on stock returns. For emphasis, the difference between our two measures of shadow rates lies in the imposition of lower bound constraint (or otherwise) for conventional (and unconventional) shadow rates. We examine how these shadow rates, as well as the conventional monetary policy measure of the Federal Reserve Bank (Fed Fund rate, FFR) behave both in the long run and short run and across different data samples.

We show that, while the shadow rate is expected to be consistent with the long-term rate, its potential for stimulating economic activity in the stock markets seems to be viable only in the short-run situation. Whether the shadow rate is bidding by the lower bound constraint or not, it tends to impact the stock market negatively in the long run, and it doesn't matter whether it is in a period of crisis or tranquility. However, even when it is impossible to lower the FFR beyond the zero bound, it still proves effective at stimulating stock returns in the long run, especially during crisis periods such as GFC and COVID-19.

Furthermore, both shadow rates (based on with or without control variables) share a common feature in virtually all 50 states in the U.S., as they show how downward-sticky the stock markets can be in the long run with a rising shadow rate, irrespective of the peculiarities of the individual states.

From a policy perspective, the study offers robust insights into the usefulness of unconventional monetary policy measures for stock market performance during crises and normal periods. Policymakers and practitioners may use this study to avail themselves of the varying short-run and long-run effectiveness of unconventional monetary policy to stimulate stock market activity.

Declaration of Competing Interest

The authors further declared as follows: This manuscript has not been submitted to, nor is under review at, another journal or other publishing venue. The authors have no affiliation with any organization with a direct or indirect financial interest in the subject matter discussed in the manuscript.

References

Aramonte, S., Lee, S. J., & Stebunovs, V. (2019). Risk taking and low longer-term interest rates: Evidence from the U.S. syndicated term loan market. *Journal of Banking & Finance*. https://doi.org/10.1016/j.jbankfin.2019.02.010

Aslam, F., Mohti, W., Ali, H., & Ferreira, P. (2023). Interplay of multifractal dynamics between shadow policy rates and stock markets. *Heliyon, 9*, Article e18114. https://doi.org/10.1016/j.heliyon.2023.e18114

Bagchi, B., & Paul, B. (2023). Effects of Crude Oil Price Shocks on Stock Markets and Currency Exchange Rates in the Context of Russia-Ukraine Conflict: Evidence from G7 Countries. *Journal of Risk and Financial Management, 16*, 64. https://doi.org/10.3390/jrfm16020064

Bampinas, G., & Panagiotidis, T. (2016). Hedging inflation with individual US stocks: A long- run portfolio analysis. *North Am J Econ Finance, 37*, 374–392.

Bauer, M. D., & Rudebusch, G. D. (2016). Monetary policy expectations at the zero lower bound. *Journal of Money, Credit and Banking, 48*, 1439–1465.

Black, F. (1995). Interest rates as options. *Journal of Finance, 50*, 1371–1376.

Bonato, M., Cepni, O., Gupta, R., & Pierdzioch, C. (2022). Climate Risks and State-Level Stock-Market Realized Volatility. University of Pretoria, Department of Economics Working. *Paper Series, 46*.

Boudoukh, J., Richardson, M., & Whitelaw, R. F. (1994). Industry returns and the Fisher effect. *J Finance, 49*(5), 1595–1615.

De Rezende, R. B., & Ristiniemi, A. (2023). A shadow rate without a lower bound constraint. *Journal of Banking & Finance, 146*, Article 106686.

Dotsis, G. (2020). Investment under uncertainty with a zero lower bound on interest rates. *Economics Letters, 188*. https://doi.org/10.1016/j.econlet.2020.108954

Gern K.J., Jannsen N., Kooths S., & Wolters M. (2015). Quantitative Easing in the Euro Area: Transmission Channel and Risks. ZBW- Leibniz Information Center of Econimics, 2015.

Gürkaynak, R., Karasoy-Can, H. G., & Lee, S. S. (2022). Stock market's assessment of monetary policy transmission: The cash flow effect. *The Journal of Finance, 77*, 2375–2421. https://doi.org/10.1111/jofi.13163

Hori, T. (2019). Monetary policy, financial frictions, and heterogeneous r&d firms in an endogenous growth model. The Scandinavian Journal of Economics, sjoe.12387–. doi:10.1111/sjoe.12387.

Iyke, B. N., & Ho, S. (2021). Exchange rate exposure in the South African stock market before and during the COVID-19 pandemic. *Finance Research Letters, 43*, Article 102000. https://doi.org/10.1016/j.frl.2021.102000

Joyce, M., Miles, D., Scott, A., & Vayanos, D. (2012). Quantitative easing and unconventional monetary policy – an introduction. F271–F288 *The Economic Journal, 122*(564). https://doi.org/10.1111/j.1468-0297.2012.02551.x.

Joyce, M., Ana, L., Ibrahim, S., & Matthew, T. (2010). The Financial Market Impact of Quantitative Easing. Bank of England Working Paper No.393.

Krippner, L. (2014). Measuring the stance of monetary policy in conventional and unconventional environments.

Kortela, T. (2016). A Shadow-Rate Model with Time-Varying Lower Bound of Interest Rates. Bank of Finland Research, Discussion Paper 19.

Korniotis, G. M., & Kumar, A. (2013). State-level business cycles and local return predictability. *Journal of Finance, 68*(3), 1037–1096.

Lemke, W., & Vladu, A. (2016). Below the Zero Lower Bound: A Shadow-Rate Term Structure Model for the Euro Area. *Discussion Paper, 32*.

Lombardi, M., & Zhu, F. (2018). A shadow rate to calibrate US monetary policy at the zero lower bound. *International Journal of Central Bank, 14*, 305–346.

Luintel, K. B., & Paudyal, K. (2006). Are common stocks a hedge against inflation. *J Financ Res, 29*(1), 1–19.

Pirinsky, C., & Wang, Q. (2006). Does corporate headquarters location matter for stock returns? *Journal of Finance, 61*, 1991–2015.

Salisu, A. A., Ndako, U. B., & Akanni, L. O. (2020a). New evidence for the inflation hedging potential of US stock returns. *Finance Research Letters, 37*, Article 101384. https://doi.org/10.1016/j.frl.2019.101384

Salisu, A. A., Raheem, I. D., & Ndako, U. B. (2020b). The inflation hedging properties of gold, stocks and real estate: A comparative analysis. *Resources Policy, 66*, Article 101605. https://doi.org/10.1016/j.resourpol.2020.101605

Salisu, A. A., Ebuh, G. U., & Usman, N. (2020c). Revisiting oil-stock nexus during COVID-19 pandemic: Some preliminary results. *International Review of Economics and Finance, 69*, 280–294.

Salisu, A. A., Isah, K., & Ogbonnaya-Orji, N. (2022). A firm-level analysis of the asymmetric response of U.S. stock returns to exchange rate movements. *International Journal of Finance and Economics, 27*(1), 1220–1239.

Swaray, R., & Salisu, A. A. (2018). A firm-level analysis of the upstream-downstream dichotomy in the oil-stock nexus. *Global Finance Journal, 37*, 199–218.

Wu, J. C., & Xia, F. D. (2016). Measuring the macroeconomic impact of monetary policy at the zero lower bound. *Journal of Money, Credit and Banking, 48*(2-3), 253–291.

Zhang, F., Narayan, P. K., & Devpura, N. (2021). Has COVID-19 changed the stock return-oil price predictability pattern? *Financ Innov, 7*, 61. https://doi.org/10.1186/s40854-021-00277-7