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Measuring the time-varying impact of conventional monetary policy on stock markets via an identified

1. Introduction

on the US stock market is almost instantaneous, and allows a better isolation of respective surprises from other sources of variations.² The adopted model framework takes both endogeneity and time varying (co)variances of interest rates and stock market returns into account. By construction, therefore, it is well suited to describe changing market conditions that underlie the changes in policy effects we intend to measure.

The monetary policy indicator that we focus on is the unexpected change in the current-month Fed funds futures rate, not the forward guidance (Fed's communication). The

basis-point cut in the Fed funds rate is associated with a 4 to 5 percent increase in stock prices in the same month. The wide range of these results might reflect either distinct methodological approaches or the analysis of empirical data drawn at different frequencies.

Variation in monetary-policy effects can inform policy planning. To proceed further, we investigate time-varying responses of stock markets in environments with different degrees of financial market stress. In a high stress market environment, financial constraints are more binding, which therefore might channel a stronger effect of the short-term rate on stock market returns. We consider a measure for credit risk to gauge states of market stress. In periods of relatively high credit risk, investors demand higher returns to compensate for higher default risks, which could limit each firm's access to credit. When the net worth of firms and borrowing conditions are affected, an interest-rate change can be expected to have stronger implications, particularly for firms (close to) facing binding financial constraints. Thus, the market's response to monetary policy will be stronger during periods of relatively high credit risk. Our results confirm that the average effects of policy on the stock market are stronger in periods of relatively high credit risk. In periods of low credit risk, stock returns increase by 1.63 percentage points to a 25-basis-point cut in the interest rate. This response increases by another 1.61 percentage points in periods of relatively high credit risk. In addition, we find that variability of the policy effect increases in periods of relatively high credit risk. We use the squared policy effect to gauge the degree of variation in the policy effects. This measure increases by 15.03 in periods of high credit risk, from 4.08 in periods of low credit risk. Therefore, during high credit risk, the response of stock returns to a 25-basis-point cut in the interest rate is 1.63 + 1.61 = 3.24 percentage points, and the variability of this response is 15.03 + 4.08 = 19.11.

The remainder of the paper is organised as follows: the next section briefly sketches the MGARCH framework and discusses the suggested approach to identification in detail. The results are presented in Section 3. Section 4 investigates the time-varying effects of monetary policy on the stock market. Section 5 examines the robustness of the results and Section 6 contains the conclusions.

changes in the monetary-policy target rate is strong and highly significant. This rate is closely related to changes in the Fed funds target rate, and this is aligned with our aim of identifying the impact of monetary policy on stock returns through unexpected changes in Fed funds rates.³ For monetary policy surprises, we use unexpected changes in the Fed funds target rate based on current-month fed funds futures contracts (from Kenneth Kuttner's website). The sample period is from 3 January 1989 to 30 December 2019.

In this section, we introduce the identified MGARCH model which specifies the link between the underlying model innovations and the heteroskedastic financial market data. Firstly, we sketch a stylised bivariate GARCH model and highlight the identification problem. Secondly, we suggest an identification approach that matches the stochastic components of the MGARCH model with market-based assessments of monetary-policy surprises.

2.1. A reduced-form MGARCH representation

Let $\mathbf{y}_t = (r_t; i_t)'$ denote a bivariate vector comprising stock returns and interest-rate changes. Multivariate GARCH processes provide a conditioning of second order moments of \mathbf{y}_t on a filtration \mathbf{F}_{t-1} that summarises system information up to time $t-1$. Formally,

$$\mathbf{y}_t = \boldsymbol{\mu}_t + \boldsymbol{\varepsilon}_t; \quad (1)$$

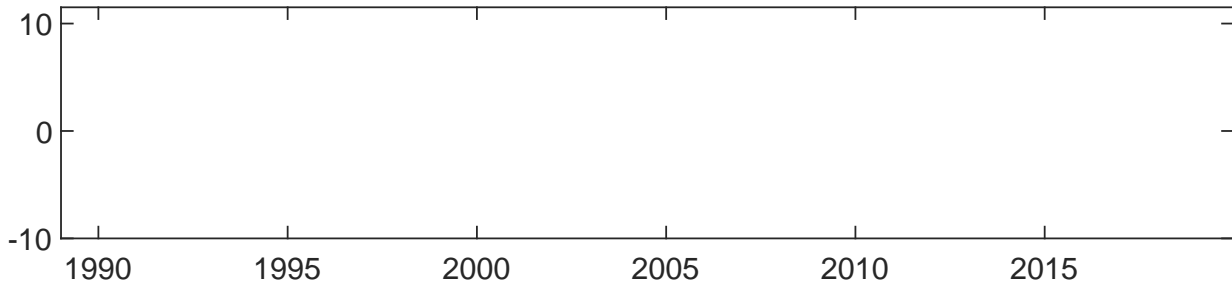
where $\boldsymbol{\mu}_t = \mathbf{E}[\mathbf{y}_t | \mathbf{F}_{t-1}]$ and, hence, $\mathbf{E}[\boldsymbol{\varepsilon}_t] = 0$.⁴ Time-varying symmetric and positive definite return covariances are denoted as

$$\text{Cov}[\boldsymbol{\varepsilon}_t | \mathbf{F}_{t-1}] = \mathbf{H}_t; \quad (2)$$

Alternative MGARCH s2 Tf 12.426 0AR

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In this specification, the identification problem is equivalent to choosing a specific rotation angle θ , which, in turn, implies a particular covariance decomposition matrix to obtain $W_t(\theta) = H_t^{1=2}(\theta)R$. The corresponding identified counterpart of the ad-hoc specification in (4) then reads as

$$e_t = W_t(\theta; \theta) \text{ iid } (0; I_N): \quad (6)$$

2.3. Identification of time varying marginal effects

Taking advantage of the informational content of policy surprises s_t , we suggest an eco-

where Σ_t is a diagonal matrix of time-varying standard deviations. With \odot denoting element-by-element multiplication, it is the case that $\Sigma_t = (\mathbf{W}_t^{-1} \mathbf{I}_N)^{-1}$ and $\mathbf{A}_t = \Sigma_t \mathbf{W}_t^{-1}$. By construction, the elements of Σ_t are uncorrelated but heteroskedastic, and the diagonal elements of \mathbf{A}_t are normalised to unity. Apparently, Σ_t are measured in the same units of the corresponding left hand side variables, i.e. percentage points. Accordingly, the off-diagonal elements in \mathbf{A}_t describe the way in which the observables in \mathbf{e}_t impact on each other contemporaneously within a feedback system. More specifically, estimates of the typical elements $a_{t,12}$ ($a_{t,21}$) quantify the time-varying marginal effects of a unit change in the second (first) element of \mathbf{e}_t on the first (second) element, conditional on the history of the process.

To formalise the novel identification scheme in the context of our empirical analysis of $\mathbf{y}_t = (\mathbf{r}_t; \mathbf{i}_t)^\theta$, let ε_{2t} denote a shock to which we wish to assign a structural interpretation (i.e. the monetary-policy shock). Evidently, the elements of Σ_t depend on the transmission matrix $\mathbf{W}_t(\cdot; \cdot)$ that allows the extraction of iid innovation vectors ε_t from the data ($\varepsilon_t = \mathbf{W}_t^{-1} \mathbf{e}_t$). To identify the stochastic model components in (7), we select the rotation angle θ , according to the following criterion:

$$= \min_{\theta} \sum_{t \in \mathcal{S}} (\varepsilon_{2t} - \mathbf{s}_t)^2; \text{ with } \varepsilon_t = (\mathbf{W}_t^{-1} \mathbf{I}_N)^{-1} \mathbf{W}_t^{-1} \mathbf{e}_t; \mathbf{W}_t = \mathbf{W}_t(\cdot; \cdot); \quad (8)$$

We chose the rotation angle(s) which minimise the sum of the squared deviations between the observed policy surprises \mathbf{s}_t and our model-implied shocks, conditional on the sample \mathcal{S} . As a result of the matching with \mathbf{s}_t , the implied shocks ε_{2t} can be considered as structural. We focus on the identification of one shock, while we leave the remaining shock ε_{1t} unidentified.

3. Empirical results

radiant and the following estimated rotation matrix⁷

$$R = \begin{pmatrix} 0.9695 & 0.2453 \\ 0.2453 & 0.9695 \end{pmatrix}$$

The corresponding estimated innovations (ϵ_{2t}) in the interest-rate equation mimic the variation of the monetary-policy surprises fairly well, see Figure 2. Regressing the estimated model innovations onto the policy surprises, s_t , yields

$$\epsilon_{2t} = 0.9886 + 0.6989 s_t + u_t \quad \text{with } \sum_{j=1}^{151} R^2 = 0.63; \\ (0.4420) \quad (0.0695)$$

with HAC robust standard errors in the parenthesis below. Thus, while the fit is good, evidence is at odds with a perfect one-to-one relation between model innovations and surprises.

The time path of the estimated policy impacts on stock markets and their corresponding bootstrap confidence intervals are sketched in the upper panel of Figure 3. It shows that the policy impacts are both negative and time-varying, with high significance. On average, estimated policy effects seem to be moderate, with the full sample median of 0.0715 percentage points. This result suggests that an unexpected 25-basis-point cut in interest rates would induce a 1.78 (25 × 0.0715) percentage-point increase in the equity index. This estimate is in the range documented by the literature on time-invariant policy impacts (1.7 percentage points in Rigobon and Sack (2004) and 1 percentage point in Bernanke and Kuttner (2005) from a 25-basis-point cut) and the time-varying approach of Paul (2020) (around 4 to 5 percentage points associated with a 20-basis-point cut). Our estimates suggest mostly moderate policy effects until the end of 2008, with a median of 1.41 percentage points. During the zero lower bound period, however, point estimates strengthen markedly. Policy effects become more erratic and confidence bands widen. The associated point estimates with a median of 4.93 percentage points seem rather large and might overstate the true effect. While such magnitudes are also found in the related literature (Paul, 2020), confidence bands are wide and include those values that appear more

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Figure 3: Conditional policy effects and respective variance shares

The figure shows the time paths of conditional policy effects a_{21t} (along with bootstrap-based 99% confidence bands) and the respective share of conditionally explained stock-market variance, obtained from the identified model in (6). Noting that the squared elements w_{ijt}^2 of W_t measure the conditional contribution of shock ϵ_{jt} to $E(\epsilon_{it}^2)$, the conditional share of explained stock-market variance attributed to the policy-shock variance is $w_{12t}^2 = (w_{11t}^2 + w_{12t}^2)$. The respective medians are indicated by dashed lines.

interest rate changes have a significantly more pronounced impact on stock markets during periods with enhanced market stress (with an increase of 2:17 percentage points in the policy effects in the post-2009 sample). The US fed funds rates converged to the zero lower bound from 2009 since the 2007-2008 financial crisis. This further strengthens the view that the market stress plays an important role in the impact of interest rates on stock markets. In addition, the degree of variation in policy effects also increases in stressful market periods. We measure this variation in terms of squared policy effects (i.e., $\alpha_{t,21}^2$). This variation increases, on average, by 15.03 in periods of relatively high credit risk, see Panel B of Table 1. Considering two sub-samples, the increase in the variation is also stronger in the post-2009 periods. Compared with average levels of 7:39 in periods of relatively low credit risk, the degree of variation in policy effects increases by 20.79 in high credit risk period.

Table 1

	Panel A: policy effect			Panel B: (policy effect) ²		
	Full	Pre-2009	Post-2009	Full	Pre-2009	Post-2009
constant	1:63 (0:04)	1:54 (0:02)	2:22 (0:12)	4:08 (0:38)	3:57 (0:15)	7:39 (1:55)
Credit Risk	1:61 (0:05)	0:10 (0:04)	2:17 (0:13)	15:03 (0:53)	2:97 (0:27)	20:79 (1:73)
R ²	0.12	0.00	0.09	0.09	0.02	0.05

Table 1
 Panel A: policy effect
 Panel B: (policy effect)²

market. In this section, we extract a common shock from suitable financial-market variables and integrate it into our model as a third variable. For this purpose, we consider the first differences of i) log exchange rates (the weighted average of the U.S. dollar value against a basket of currencies), ii) log gold prices, and iii) log crude oil prices.⁸ From these log differences we obtain the first principal component (denoted as \mathbf{c}_t) to approximate a common exogenous factor that might induce joint movements in asset prices including stock-market and interest-rate variation. It is integrated into a corresponding trivariate GARCH model with $\mathbf{y}_t = (r_t; i_t; \mathbf{c}_t)'$. We then identify the policy effects as before, while treating the remaining two shocks in an agnostic manner.

Our results show that the estimated policy effects from the trivariate model are similar to those from the bivariate model. The correlation between the two is 0.99. A 25-basis-point cut in the interest rate would induce a median increase in the stock index of 1:78 percentage points in the bivariate model and 1:62 percentage points in the trivariate model. The results of the time-varying policy effects are also similar, and are documented in Table 2. In periods of relatively large credit risk, the policy effect on the market is stronger and the variation of the policy effect also increases. From 2009 onward, this pattern becomes stronger.

using an identified multivariate GARCH model, in which the heteroskedasticity of shocks in both interest rates and stock markets are taken into account. We use the informational content embedded in the monetary-policy surprises on event days to identify the market's response to monetary policy, and enable the estimation of time-varying policy effects on the market.

Our results show that a cut of 25 basis points in the interest rate would induce a median 1.78 percent increase in the equity index. Furthermore, during periods of relatively large credit risk, the monetary-policy effects on the stock market are stronger and the variation of the policy effect is larger.

A potential direction for future research, based on the approach of this paper, would be out-of-sample forecasting. Our methodology enables predictions of asset-market reactions to an unexpected policy interest-rate change to be made, based on the most recent market conditions. Because covariance modelling/prediction works well for financial market data, one might expect good out-of-sample forecasting of policy effects.

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