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The State-dependent Trading Behavior of Banks in the Oil Futures Market*

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Abstract

We study the state-dependent trading behavior of financial institutions in the oil futures market, using structural vector autoregressions with Markov switching in heteroskedasticity. We consider two states of the world: tranquil and turbulent. We decompose the observable time-varying price volatility during the period 2006M6-2016M5 into changes in the slopes of traders' demand curves and into changes in the variability of their demand shocks. We find that the downward-sloping demand curve of intermediaries steepens significantly during crises times and that the variance of their demand shocks doubles. These findings suggest that the futures pricing of financial institutions is highly nonlinear and raises the hedging costs of producers and consumers of oil when volatility is high.

JEL Classification: C32, G12, G21, Q02.

Keywords: Asset pricing; trading behavior; financial institutions; vector autoregressions; market microstructure; oil markets.

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1 Introduction

Traditional theories of asset pricing assign no role to financial intermediaries and view them as a veil without influence on the functioning of financial markets. This conjecture has been questioned. Modern finance states that intermediaries, broadly defined as entities which channel funds between different parties, affect asset prices due to several frictions (Shleifer and Vishny, 1997, Kyle and Xiong, 2001). Following the global financial crisis, Brunnermeier and Pedersen (2009) and He and Krishnamurthy (2013) show theoretically how asset price dynamics may change during crises in markets where intermediaries are the marginal investors. Under financial stress, intermediaries' funding constraints can become binding and their risk-bearing capacity may shrink. Such occasionally binding constraints lay the foundation for nonlinearities and give rise to liquidity dry-ups and volatility spikes. Based on these theoretical insights, several empirical papers study the relation between cross-sectional asset pricing and various measures of intermediaries' financial health (Adrian et al., 2014, He et al., 2017).

There is also an intense debate about the increased presence of financial institutions in commodity markets and whether they amplify commodity price fluctuations (Irwin and Sanders, 2012, Hamilton and Wu, 2015, Pavlidis et al., 2018). Sanders and Irwin (2013), for instance, assess the accuracy of the imputed amount of index investments in the WTI crude oil futures market, which allows gauging the importance of these financial investments in commodity markets; Acharya et al. (2013) show that the severity of intermediaries' capital constraint affects futures risk premia; and Etula (2013) highlights the relevance of the risk-bearing capacity of securities broker-dealers for futures risk premia.

In this paper, we study the state-dependent trading behavior of financial intermediaries in the oil futures market and the quantitative implications for changes in futures price volatility. We build a Markov switching in heteroskedasticity structural vector autoregressive (MSH-SVAR) model and estimate it on weekly position data from the U.S. Commodity Futures Trading Commission (CFTC). The sample period is June 2006 until May 2016. Our proxy for intermediaries' exposure are futures positions held by large global banks, such as JP Morgan Chase, Goldman Sachs, or Morgan Stanley. For identification of the structural model, we use a stylized conceptual framework following Cheng et al. (2015). It describes the trading behavior of different trader groups in form of net long demand curves depending on the contemporaneous futures price and a group-specific demand shock. The framework provides sufficient restrictions for just-identification. The main identifying assumption is that traders do not respond directly to position changes of other trader groups, consistent with the publication lag of the CFTC data.

We consider two states of the world: tranquil and volatile periods. The endogenous determination of these states is at the core of the analysis. The Markov switching framework gives full voice to the data and reduces the risk of misspecification of the transition

points. Since the structural model is just-identified for each state, we can let both the impact effects and the volatility of the structural shocks switch across states. This facilitates a decomposition of reduced-form changes in futures price volatility into changes in the slopes of traders' demand curves and in the volatility of their demand shocks.

Our paper contributes to the literature along several dimensions. The results show that the trading behavior of financial intermediaries changes significantly across states. First, the demand curve of intermediaries steepens significantly when switching from the tranquil to the turbulent state. The lower price elasticity implies that they are less willing or able to absorb trades of other market participants. This increases the hedging costs for producers, processors, and consumers of oil by two thirds according to our estimates. Second, the variance of intermediaries' own demand shocks doubles during these episodes. This raises price volatility further. Both findings are consistent with the theoretically predicted nonlinearities in Brunnermeier and Pedersen (2009) and He and Krishnamurthy (2013).

Our study also relates to a long-standing literature on the determination of commodity futures prices, and their relation to spot prices.[1] Recently, there has been much interest in the role of financial institutions in these markets and whether the increased presence of financial investors has changed the functioning of commodity markets (Fattouh et al., 2013, Cheng and Xiong, 2014). Our analysis focuses on the role of financial intermediaries in the price formation process on the oil futures market. We show that their trading behavior is state-dependent and that this increases the hedging costs of other market participants significantly when volatility is high, that is, when hedging is needed most.

The paper builds on a literature on structural time-series models with heteroskedasticity (Rigobon, 2003). We combine the type of Markov switching models following Herwartz and Lütkepohl (2014) with the framework of Bacchiocchi and Fanelli (2015) and Bacchiocchi (2017). The first model type determines regime switches endogenously, but allows only for changes in the volatility of the structural shocks across regimes. The second class allows for changes in both the contemporaneous effects and the volatility of the structural shocks, but defines the regimes exogenously based on prior information. Our model contains both desirable features: an endogenous regime determination, and changes in the impacts and in volatility. This is crucial for our analysis as it allows, first, endogenously estimating switches in volatility and, second, decomposing them into changes in the slopes of demand curves and into changes in the volatility of demand shocks. Another important difference to the aforementioned models is that we do not use the heteroskedasticity for identification. The latter is achieved through economic reasoning, implying that the structural shocks have the simple economic interpretation of net long demand shocks.

[1] See Garbade and Silber (1983), Hirshleifer (1990), Kilian and Murphy (2014), Henderson et al. (2015), Sockin and Xiong (2015).

The model is also easily interpretable, in that, conditional on the state, it is identical to a single state model.

Finally, we investigate whether combinations of variables can capture the Markov switching regimes. We relate the smoothed probability of the high volatility state to model-external variables through logit regressions. They show that higher Baa-Aaa corporate bond spreads and lower U.S. Treasury yields are the best indicators of turbulent times, consistent with risk premia and risk-free rates being important factors for the futures basis and prices (Gorton et al., 2012, Szymanowska et al., 2014).

The remainder of the paper is structured as follows. The next section discusses the literature on intermediary asset pricing, presents a simple conceptual framework and some testable implications. It further outlines the empirical methodology and describes the data. Section 3 contains the main results, while Section 4 provides further evidence on the characteristics of the high volatility state. This section also contains an extensive sensitivity analysis. The last section concludes.

2 Conceptual Framework, Empirical Model and Data

In this section, we first summarize the literature on intermediary asset pricing. Using the findings in the literature, we present a conceptual framework and derive two testable implications for the trading behavior of intermediaries in the oil futures market. The section ends with a description of the data.

2.1 Conceptual Framework

Traditional theories of asset pricing regard financial intermediaries as a veil without influence on the performance of asset markets. Intermediaries act according to their clients' preferences, making a representative household the marginal investor. This neglect of the intermediary sector has been questioned by numerous studies showing that intermediaries face a variety of constraints, such as limits to arbitrage, due to which they influence the functioning of asset markets (Kyle and Xiong, 2001, Fostel and Geanakoplos, 2008). In an influential paper Brunnermeier and Pedersen (2009) show the interdependence between the ability of intermediaries to raise capital and market liquidity. If funding liquidity is scarce, intermediaries are reluctant to open new positions, market liquidity is lower, and volatility is higher. He and Krishnamurthy (2013) study the asymmetric effects of intermediary capital on risk premia. When capital is abundant, intermediaries are able to offset losses such that there are limited effects on risk premia. When capital is scarce, however, intermediaries' losses can be associated with higher and more volatile risk premia.

The subsequent empirical literature has studied the relation between intermediaries' financial health, using a variety of approximations of this unobservable variable, and asset

prices. Adrian et al. (2014) investigate the relation between a stochastic discount factor based on the leverage of security broker-dealers and asset returns. He et al. (2017) use capital ratios of intermediaries and provide evidence that intermediaries are the marginal investors in many asset markets and thus key to understanding price formation. Focusing on commodity markets, Acharya et al. (2013) show that the futures risk premium and hence producers' hedging costs are increasing in the severity of intermediaries' capital constraints, measured by their assets relative to households' assets. Etula (2013) uses the leverage of securities broker-dealers, who serve as counterparties to hedgers, to build a risk aversion index and finds that it is a determinant of risk premia in commodity futures markets. Finally, Cheng et al. (2015) approximate the risk absorption capacity of financial traders in commodity futures markets with the VIX and document a risk transfer from those traders to hedgers during periods of high volatility.

These contributions suggest that when volatility is high (i) intermediaries are more reluctant to take on new positions, and (ii) their exposure to idiosyncratic balance sheet shocks increases. To map these considerations into testable implications, we formulate a stylized model of the oil futures market, following Cheng et al. (2015). The framework describes the trading behavior of all market participants, who are assumed to be atomistic price takers. We distinguish between three groups of traders: hedgers (H), financial intermediaries (F), and others (O). Hedgers are producers, processors, or large consumers of oil, who want to hedge physical oil price risk of commercial businesses. For the second group, we primarily think of it as large banks that either trade on behalf of clients without direct access to the futures market or on their own behalf. The third group contains all remaining traders and is mainly comprised of specialized commodity trading advisors, commodity pool operators, and traders who cannot be clearly classified in any other category.

The demand curves of the three trader groups are

$$\begin{aligned}
\Delta y^H &= -a^H(S)\Delta P + \sqrt{\lambda^H(S)}\nu^H \\
\Delta y^F &= -a^F(S)\Delta P + \sqrt{\lambda^F(S)}\nu^F \\
\Delta y^O &= -a^O(S)\Delta P + \sqrt{\lambda^O(S)}\nu^O,
\end{aligned}$$

where Δy^i denotes the change in the net long oil futures position of trader group $i = H, F, O$. ΔP is the log difference in the oil futures price. The coefficients $a^i(S)$ determine the slope of the respective demand curve and thus measure the price elasticity of each group. They reflect the capacity or willingness to absorb trades of other groups.

Illiquidity might arise if there are limits to arbitrage which deter risk averse arbitrageurs from taking the counter-side. Shleifer and Summers (1990) and Shleifer and Vishny (1997), for example, show that large position changes can influence prices through an effect on the order book if the instantaneous supply of counterparty orders is low.

Regarding financial intermediaries, a low a^F implies that they absorb a smaller part of the desired demand shift of producers or, equivalently, provide less liquidity, and that the price impact will be larger.

Each demand curve further features a random shock ν^i which causes the respective trader group to adjust its net long position due to own reasons. For financial intermediaries the causes can be manifold: portfolio diversification, risk management, speculative motives based on private signals, or long hedging of short exposure vis-à-vis clients. The $\lambda^i(S)$'s measure the variances of the shocks and are allowed to differ across groups. One can interpret these coefficients as the exposure of each trader group to its idiosyncratic shocks. For example, if we think of ν^F as a shock hitting the balance sheet of intermediaries, then a larger λ^F suggests a greater exposure to this shock. Although being highly stylized, the simple demand functions thus capture two main trading motives of financial institutions in commodity futures markets: liquidity provision to other traders and trading for own purposes. The market clearing condition, $\Delta y^H + \Delta y^F + \Delta y^O = 0$, closes the model and ensures that the price is jointly determined by all traders in equilibrium.

We distinguish in an ad-hoc form between two different states $S = 1, 2$ of the world. Without loss of generality, we think of state 1 as tranquil periods and of state 2 as volatile times. The latter can be either episodes of general financial market turmoil that spill over to the oil futures market through balance sheets of intermediaries or drastic oil market developments that directly affect intermediaries in the oil futures market. The central feature of the model is that the $a^i(S)$ and $\lambda^i(S)$ coefficients are allowed to differ between regimes. Hence, both the ability of traders to absorb other traders' shocks as well as the variance of own shocks can change between states. Using the market clearing condition and writing the system in matrix notation gives

$$\begin{pmatrix} 1 & 0 & a^H(S) \\ 0 & 1 & a^F(S) \\ -1 & -1 & a^O(S) \end{pmatrix} \begin{pmatrix} \Delta y^H \\ \Delta y^F \\ \Delta P \end{pmatrix} = \begin{pmatrix} \sqrt{\lambda^H(S)}\nu^H \\ \sqrt{\lambda^F(S)}\nu^F \\ \sqrt{\lambda^O(S)}\nu^O \end{pmatrix}. \tag{1}$$

The inclusion of these endogenous variables allows us to capture the most relevant players in the oil futures market. Including an additional group "Other Reportables" as a robustness exercise does not influence our findings. Expression 1 is the basis for the identification of our structural empirical model. It illustrates our main identifying restrictions which are reflected in the zero elements on the LHS of (1). We assume that no trader group responds directly to the position change of any other group. This assumption is consistent with the publication lag of the CFTC data that we use and the market to which they refer. The positions correspond to each Tuesday end-of-day at the electronic trading platform of the New York Mercantile Exchange. Here, aggregated orders of the other investors are not observable. Furthermore, the CFTC reports are only

released the following Friday, implying that traders cannot contemporaneously observe and thus directly respond to aggregated position changes of other groups. They do so, of course, indirectly through prices.

Given our interest in financial intermediaries, we derive the following hypotheses about the changes in the coefficients across states:

Hypothesis 1 *The slope of the demand curve of financial intermediaries changes during turbulent times:* $a^F(1) \neq a^F(2)$.

Hypothesis 2 *The volatility of intermediaries' demand shifts changes during turbulent times:* $\lambda^F(1) \neq \lambda^F(2)$.

The alternative hypotheses are that there are no significant changes across regimes, implying that there is no clear difference in the way financial intermediaries trade in tranquil versus turbulent times. Finally, unlike Cheng et al. (2015), our framework does not contain a common shock which simultaneously affects all trader groups. This reduces the computational complexity of the estimation. Instead, we deal with such shocks by including a number of exogenous control variables in the baseline empirical model and by conducting an extensive sensitivity analysis adding further controls.

2.2 The MSH-SVAR Model

We now describe the Markov switching in heteroskedasticity vector autoregressive (MSH-VAR) model, which treats any potential transition variable(s) as latent. Specifically, we follow the approach of Herwartz and Lütkepohl (2014), where only the reduced form covariance matrix may change across volatility regimes and all other parameters are held constant. The authors attribute these changes to changes in the variances of the structural shocks and use them for identification, holding constant the contemporaneous effects of the shocks across regimes. We depart from their model along two important dimensions. First, we do not use the heteroskedasticity in the data for identification. We achieve the latter through economic reasoning, exploiting the parameter restrictions implied by the theoretical model of Section 2.1. Second, given that our model is just-identified for each state, we allow for changes in both the contemporaneous effects and in the variances of the structural shocks.

The reduced form model is given by

$$y_t = c + \Gamma_1 y_{t-1} + \cdots + \Gamma_p y_{t-p} + \Psi_0 x_t + \Psi_1 x_{t-1} + \cdots + \Psi_n x_{t-n} + u_t, \tag{2}$$

where $y_t = [\Delta y_t^H, \Delta y_t^F, \Delta P_t]'$ is the vector of endogenous variables with Δy_t^H and Δy_t^F the change in the net long futures position of hedgers and financial intermediaries, respectively,

and ΔP_t the log difference in the oil futures price. Further, x_t is a vector of W exogenous variables discussed below, Γ_i and Ψ_j are parameter matrices with $i = 1, \ldots, p$ and $j = 1, \ldots, n$, where n does not necessarily equal the lag length p, and c is a vector of constants. Finally, u_t is a vector of reduced form error terms with $\mathbb{E}[u_t] = 0$ and $\mathbb{E}[u_t u_t'] = \Sigma_u(S_t)$. For estimation purposes, we assume that u_t is normally and independently distributed conditional on a given state:

$$u_t | S_t \sim \text{NID}(0, \Sigma_u(S_t)).$$

Here, S_t is a first order discrete valued Markov process that can take on M different values, $S_t = 1, \ldots, M$, with transition probabilities $p_{kl} = P(S_t = l | S_{t-1} = k), k, l = 1, \ldots, M$. Although the model is linear in a given state, it is nonlinear as a whole.

Using the conceptual model in (1), we write the structural empirical model as

$$\underbrace{\begin{bmatrix} 1 & 0 & a^H(S_t) \\ 0 & 1 & a^F(S_t) \\ -1 & -1 & a^O(S_t) \end{bmatrix}}_{\equiv A(S_t)} \underbrace{\begin{bmatrix} \Delta y_t^H \\ \Delta y_t^F \\ \Delta P \end{bmatrix}}_{= y_t} = \begin{bmatrix} \epsilon_t^H \\ \epsilon_t^F \\ \epsilon_t^O \end{bmatrix}, \tag{3}$$

where $\epsilon_t = [\epsilon_t^H \ \epsilon_t^F \ \epsilon_t^O]'$ is a vector of structural shocks whose standard deviations correspond to $\sqrt{\lambda^i}$ in the conceptual model, and where we have neglected constants, lags and exogenous variables for illustration.[2] This leads to the following relationship between the reduced form errors and the structural shocks: $u_t = A(S_t)^{-1}\epsilon_t$, where $A(S_t)^{-1}$ is a matrix of state-dependent instantaneous effects.

It is important that despite the zeros in $A(S_t)$ all variables are allowed to react contemporaneously to all shocks since

$$A^{-1}(S_t) = \begin{bmatrix} \frac{a^F(S_t)+a^O(S_t)}{\tilde{a}(S_t)} & -\frac{a^H(S_t)}{\tilde{a}(S_t)} & -\frac{a^H(S_t)}{\tilde{a}(S_t)} \\ -\frac{a^F(S_t)}{\tilde{a}(S_t)} & \frac{a^H(S_t)+a^O(S_t)}{\tilde{a}(S_t)} & -\frac{a^F(S_t)}{\tilde{a}(S_t)} \\ \frac{1}{\tilde{a}(S_t)} & \frac{1}{\tilde{a}(S_t)} & \frac{1}{\tilde{a}(S_t)} \end{bmatrix}, \tag{4}$$

where $\tilde{a}(S_t) = a^H(S_t) + a^F(S_t) + a^O(S_t)$. This is a central feature of the model and a main building block of the empirical plausibility of our identifying assumptions as traders respond to each other through prices in nearly continuous time. Any zero restrictions on $A^{-1}(S_t)$ would thus be difficult to justify. The structure of $A^{-1}(S_t)$ follows from the restrictions on $A(S_t)$ and reveals that a change of $a^F(S_t)$ across states affects the response of all variables to all shocks as it enters the denominator of all elements in $A^{-1}(S_t)$.

[2] Implicitly this means that $\nu^i \sim (0, 1)$ and that $\epsilon^i \equiv \sqrt{\lambda^i(S)}\nu^i \sim (0, \lambda^i(S))$.

In order to allow for state-dependence of the instantaneous effects we model $A(S_t)$ as

$$A(S_t) = \bar{A} + \mathcal{A}(S_t), \quad S_t = 1, \ldots, M, \tag{5}$$

where $\bar{A}$ consists of the state-invariant part and $\mathcal{A}(S_t)$ is the state-dependent part of the matrix. For simplicity, we set $\mathcal{A}(1) = 0$. To summarize, the definitions are

$$A(S_t) = \begin{bmatrix} 1 & 0 & a^H(S_t) \\ 0 & 1 & a^F(S_t) \\ -1 & -1 & a^O(S_t) \end{bmatrix}, \quad \bar{A} = \begin{bmatrix} 1 & 0 & \bar{a}^H \\ 0 & 1 & \bar{a}^F \\ -1 & -1 & \bar{a}^O \end{bmatrix}, \quad \mathcal{A}(S_t) = \begin{bmatrix} 0 & 0 & \alpha^H(S_t) \\ 0 & 0 & \alpha^F(S_t) \\ 0 & 0 & \alpha^O(S_t) \end{bmatrix}. \tag{6}$$

Further, we assume that the structural errors have a non-identity diagonal covariance matrix: $E[\epsilon_t \epsilon_t'] = \Lambda(S_t)$ (naturally $E[\epsilon_t] = 0$). We allow this matrix to be state-dependent in an analogous fashion as above

$$\Lambda(S_t) = \bar{\Lambda} + \tilde{\Lambda}(S_t), \quad S_t = 1, \ldots, M, \tag{7}$$

where each matrix is diagonal. The orthogonality of the structural errors is required for identification of the structural parameters and is reasonable for idiosyncratic shocks. We use a variety of endogenous control variables in order to control for any common shocks. A typical element of $\Lambda(S_t)$ is $\lambda^i(S_t) = \bar{\lambda}^i + \ell^i(S_t)$, where $\bar{\lambda}^i$ and $\ell^i(S_t)$ are the respective elements of $\bar{\Lambda}$ and $\tilde{\Lambda}(S_t)$. Again, for simplicity, we set $\tilde{\Lambda}(1) = 0$. The covariance matrix of the reduced form errors can then be written as

$$\Sigma_u(S_t) = A(S_t)^{-1} \Lambda(S_t) (A(S_t)^{-1})' \, . \tag{8}$$

The system contains six structural parameters per state. These can be directly mapped to the six unique reduced form parameters through (8). The model is thus just-identified for any M; due to restrictions based on economic reasoning, without relying on changes in volatility. This approach uses a combination of established approaches found in the literature. For instance, the decomposition in (8) is used by Lanne et al. (2010), Herwartz and Lütkepohl (2014) and others.

In addition, analogous decompositions as in (5) and (7) can be found in Bacchiocchi and Fanelli (2015) and Bacchiocchi (2017), which allow for both changes in the structural slope parameters and changes in the structural shock variances. We follow the approach suggested by these authors, to check for (local) identification of the model, given the set of restrictions that we impose. Specifically, the necessary and sufficient rank condition for local identification is satisfied if the $K(K+1) \times a$ matrix given by

$$\begin{pmatrix} I_2 \otimes D_K^+ \end{pmatrix} = \begin{pmatrix} 2(\bar{A}^{-1} \otimes I_K) & 0_{K^2 \times K^2} & 0_{K^2 \times K} \\ 2[((\bar{A}+\mathcal{A})^{-1})\Lambda \otimes I_K] & 2[((\bar{A}+\mathcal{A})^{-1})\Lambda \otimes I_K] & [((\bar{A}+\mathcal{A})^{-1}) \otimes ((\bar{A}+\mathcal{A})^{-1})]U_K' \end{pmatrix} S \tag{9}$$

has full column rank.[3]

2.3 Estimation and Bootstrap Procedure

The parameters in (2) are estimated by means of the expectation maximization (EM) algorithm of Hamilton (1994, Ch. 22), which was extended to multivariate processes by Krolzig (1997). Crucial for the analysis is to incorporate the regime-switching nature of the covariance matrix described in (5) and (7), given the restrictions in (6). The latter do not contain any sign restrictions on the coefficients $a^i(S)$. As in Podstawski and Velinov (2018), we use the following concentrated out log likelihood function in the maximization step of the EM algorithm:

$$\begin{aligned} l(\bar{A}, \mathcal{A}(2), \ldots, \mathcal{A}(M), \bar{\Lambda}, \tilde{\Lambda}(2), \ldots, \tilde{\Lambda}(M)) &= \frac{1}{2} \sum_{m=1}^{M} \Bigg[\widehat{T}_m \log(\det(\Sigma_u(m))) \\ &\quad + \operatorname{tr}\left((\Sigma_u(m))^{-1} \sum_{t=1}^{T} \widehat{\xi}_{mt|T} \widehat{u}_t \widehat{u}_t' \right) \Bigg], \end{aligned}$$

where $\Sigma_u(m)$ is defined as in (8). Further, $\xi_{mt|T}, m = 1, \ldots, M,\ t = 1, \ldots, T$ are the model smoothed probabilities, $T_m = \sum_{t=1}^{T} \xi_{mt|T}$, and the hat symbol denotes estimated parameters obtained from the previous iteration.

Once the EM algorithm has converged, we obtain standard errors of the point estimates of the parameters through the inverse of the negative Hessian matrix evaluated at the optimum. We use these standard errors as a first statistic to determine whether the estimated parameters change significantly across states. As a second statistic, we use Likelihood Ratio tests, where we restrict the main parameters of interest to be time-invariant. As a third statistic, we compute bootstrapped impulse responses. Given the heteroskedasticity, classical residual bootstrapping may be problematic in generating reliable confidence intervals. Any re-sampling scheme needs to preserve the second order characteristics of the data. We therefore use a fixed design wild bootstrap with $u_t^\star = \varphi_t \widehat{u}_t$, where φ_t is a random variable independent of y_t following a Rademacher distribution. That is, φ_t is either 1 or –1 with probability 0.5. This is a common technique for these

[3] K is the number of endogenous variables; $a := a_{\bar{A}^{-1}} + a_{\mathcal{A}} + a_{\Lambda}$; $a_{\bar{A}^{-1}}$, $a_{\mathcal{A}}$, a_{Λ} is number of free elements of $\bar{A}^{-1}, \mathcal{A}$ and Λ, respectively; $S_{\bar{A}^{-1}}$, $S_{\mathcal{A}}$, and S_{Λ} summarize linear restrictions on $\bar{A}^{-1}$, $\mathcal{A}$ and Λ, respectively; S_I summarizes cross-restrictions on the elements of $\bar{A}^{-1}$ and $\mathcal{A}$; D_K^+ is the Moore-Penrose inverse of the duplication matrix D_K; and

$$S = \begin{pmatrix} S_{\bar{A}^{-1}} & S_I & 0_{K^2 \times a_\Lambda} \\ 0_{K^2 \times a_{\bar{A}^{-1}}} & S_{\mathcal{A}} & 0_{K^2 \times a_\Lambda} \\ 0_{K^2 \times a_{\bar{A}^{-1}}} & 0_{K^2 \times a_{\mathcal{A}}} & S_\Lambda \end{pmatrix}. \tag{10}$$

As suggested by Bacchiocchi and Fanelli (2015), we check numerically whether the matrix (9) has full rank before estimation by drawing 100,000 matrices $\bar{A}, \mathcal{A}, \Lambda$ from the uniform distribution on the interval between -10 and 10. We find that the rank condition is satisfied for all draws.

types of models (Herwartz and Lütkepohl, 2014, Podstawski and Velinov, 2018). All the computations are done with the software Matlab.

2.4 Data

We use data of the Disaggregated Commitments of Traders (DCOT) Report of the U.S. Commodity Futures Trading Commission (CFTC). The data are weekly and are available from 13 June 2006 onwards. Our sample ends on May 24, 2016, thereby containing 520 observations. It is characterized by two severe oil price collapses: the gloabal financial crisis and the oil price recession in 2014/16. This needs to be kept in mind when interpreting our estimates as they may not be representative of the more tranquil period prior to the global financial crisis.

We calculate the net long position of the trader groups denoted as "Producer/ Merchant/ Processor/ User" and "Swap Dealer" in light sweet crude oil traded at the New York Mercantile Exchange (NYMEX) to approximate net long demand of hedgers and financial intermediaries, respectively. Given the computational complexity of the empirical model we focus on these two trader groups, as they have relatively well defined business models within classifications, and lump the remaining groups in the price equation. In Section 4.2, we show that the results are insensitive to adding another trader group to the model. We employ the next-to-maturity futures settlement price of light crude oil at NYMEX. The endogenous variables enter the model in standardized first differences and in log differences for prices.

According to the definition of the CFTC, a swap dealer is "[a]n entity that deals primarily in swaps for a commodity and uses the futures markets to manage or hedge the risk associated with those swaps transactions" (CFTC, 2017a). The vast majority of them are major global banks and the remaining traders in this group are other banks and financial intermediaries (CFTC, 2017b). Heumesser and Staritz (2013) document that the four largest globally active banks in this category held around 70% of swap positions in commodity futures markets in 2008, namely, Goldman Sachs, Morgan Stanley, JP Morgan, and Barclays Bank. In 2012 the group was made up of Bank of America, JP Morgan, Goldman Sachs, and Citibank. Other banks with big swap positions include Merril Lynch, Deutsche Bank, HSBC, Credit Suisse, Rabobank, and UBS.

One caveat of the CFTC data are potential misclassifications of traders and hence reporting errors. First, financial intermediaries have incentives to be classified as hedgers since this entitles them to preferential treatments. Hedgers are exempted from position limits and face lower margins requirements, translating into less capital needed for maintaining open positions. Second, the data refer to total end-of-day positions of traders, meaning that positions are aggregated across trades due to different business reasons. This aggregation complicates an interpretation of position changes. Third, the CTFC

itself changes the classification of traders from time to time, for example following alterations in the way traders participate in the futures market. Overall, misclassifications cannot be fully excluded. But the bias of these reporting errors is likely to imply that some financial traders are erroneously classified as hedgers and our results might then actually represent a lower bound of the influence of intermediaries on futures prices.

Finally, we augment the model with a number of contemporaneous exogenous variables to control for common factors that potentially affect positions of all trader groups simultaneously. We add the number of initial jobless claims to capture the state of the real economy and the balance sheet of the Federal Reserve to account for nominal developments. Both variables are available at the weekly frequency. Moreover, we include the surprise component in news releases of 30 U.S. macroeconomic indicators to account for public information approaching the market. In Section 4.2 we show that the results are insensitive to the inclusion of a large number of further exogenous variables. Appendix A contains a complete description of the data used in the analysis.

3 Results

We start by showing statistical evidence supporting the choice of a regime-switching model, followed by a brief presentation of the endogenously determined states. We then discuss the model's main implications in terms of estimated structural parameters. Additionally, we report bootstrapped impulse responses and variance decompositions.

3.1 Model Selection

We follow the literature and select the lag order of the endogenous variables in the MSH-VAR model based on a linear VAR model. All three information criteria point to one lag out of 26 considered lags. This also seems plausible from an economic point of view, given that financial markets react immediately to new information, and since our data are of weekly frequency. We use the same lag length for the exogenous variables.

Table 1 contains specification statistics for the Markov switching model. It shows that a MSH-VAR model is clearly preferred over a standard linear VAR according to the log-likelihoods and information criteria. The latter have been shown to work well to judge the performance of MS models (Psaradakis and Spagnolo, 2006), whereas standard tests are problematic for determining the number of states (Hansen, 1992). The choice of two states is motivated by theoretical reasoning (see Section 2). This number suffices to test our two hypotheses. Estimation of a two-state model is also less cumbersome and leads to more stable and precise estimates, given that a potential third state contains only a limited number of observations. Nevertheless, we consider a three state model in the robustness analysis.

Table 1: Model Specification

Model	Log Likelihood	AIC	SC
Reduced form linear VAR	−2069.4	4354.7	4813.7
Reduced form MSH-VAR, 2 states	−1957.2	4158.3	4676.8

Note: Model fit comparison of a linear VAR and a two-state MSH-VAR with lag order $n = p = 1$ based on the log-likelihood, Akaike information criterion, and Schwarz criterion.

Finally, we do not consider a model with switches in the conditional mean, which is a nonlinear function of both the intercept and all the parameters on the lagged variables, as programming and estimating such a model is challenging. In the sensitivity analysis, we show that the main results are unchanged when considering a switching intercept term.

3.2 Volatility regimes

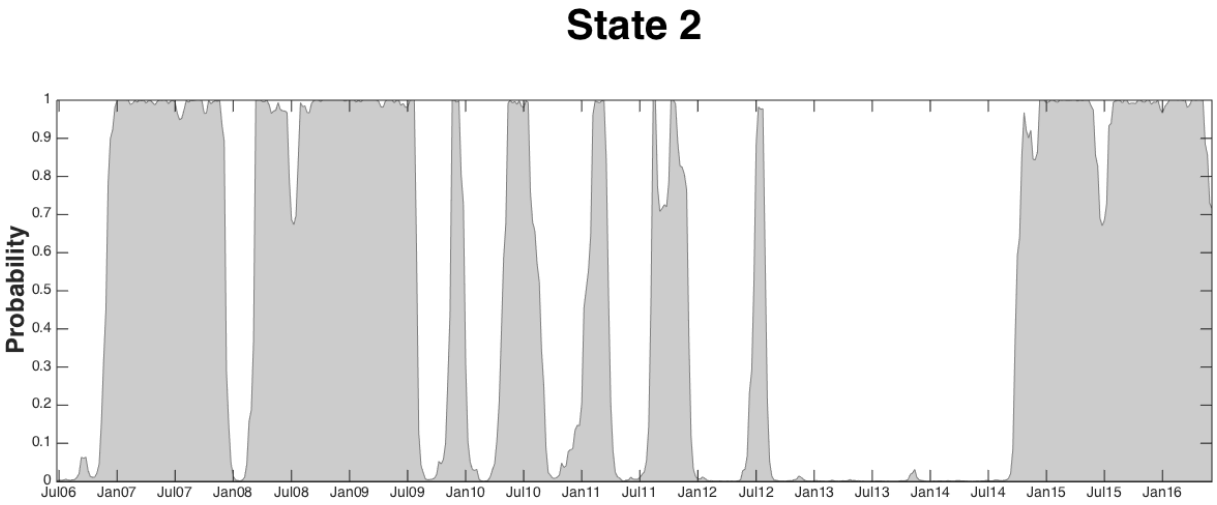
One main feature of the Markov switching model is the endogenous determination of the two states based on changes in the reduced form covariance matrix. For the labeling of the states we look at the diagonal elements of the reduced form covariance matrices:

$$\Sigma_u(1) = \begin{pmatrix} 0.58 & \cdot & \cdot \\ 0.00 & 0.74 & \cdot \\ -0.11 & -0.33 & 0.31 \end{pmatrix} \qquad \Sigma_u(2) = \begin{pmatrix} 1.34 & \cdot & \cdot \\ -0.29 & 0.78 & \cdot \\ -0.23 & 0.05 & 1.58 \end{pmatrix}. \tag{11}$$

Equation (11) shows that there is a low-volatility regime, state 1, with relatively small variances, and a high-volatility regime, state 2, with larger variances. Especially the variance of the oil futures return increases strongly from 0.31 to 1.58 in state 2. The variance of net long positions of hedgers also more than doubles from 0.58 to 1.34. In contrast, the variance of net long positions of financial intermediaries increases only mildly from 0.74 to 0.78. Through the lens of the conceptual model, this modest change is likely reflecting two offsetting forces. On the one hand, a steeper demand curve of intermediaries (Hypothesis 1) means that they are less price-elastic and implies that a given order of other market participants induces a smaller change in intermediaries' positions and a larger price increase. On the other hand, a rise in the volatility of intermediaries' own demand shocks (Hypothesis 2) is tantamount to a rise in the variance of their positions. Together, we thus observe a small increase in the variance of intermediaries' positions and a large increase in the variance of the price in state 2. In the following we refer to state 1 as the "tranquil state" and to state 2 as the "turbulent state."

Figure 1 plots the smoothed probabilities of state 2. They show that the model distinguishes the two volatility states well throughout the sample. The probability of being in the high volatility state 2 is either (very close to) 100% or (very close to) 0%.

Figure 1: Smoothed Probabilities of State 2



Note: Plot of the endogenously estimated smoothed probabilities of the high volatility state 2, that is, the "turbulent state."

This clear distinction can be interpreted as a validation of the assumption of switching volatility over time. Furthermore, there are ample observations in each state, providing the basis for an estimation of the state-specific parameters.

3.3 State-Dependent Intermediary Pricing

In the following we formally test our two main hypotheses by evaluating the estimated parameters of interest, and their statistical significance based on the Hessian. We also perform Likelihood Ratio tests to compare the baseline specification allowing for switches in all parameters with alternative models which restrict some to be time-invariant.

We start with the estimated relations between variables in the tranquil state:

$$A(1) = \bar{A} = \begin{pmatrix} 1 & 0 & 1.06^{***} \\ & & (0.22) \\ 0 & 1 & 1.52^{***} \\ & & (0.13) \\ -1 & -1 & 0.56 \\ & & (0.53) \end{pmatrix}.$$

The matrix corresponds to the one in the conceptual model and the last column contains the estimated slopes of the demand curves. For the interpretation, the sign of the coefficients needs to be reversed to obtain the estimated price elasticity (see 3). Hedgers are ordered first, financial intermediaries second, and the group of others third. The values in parentheses show the standard errors. Asterisks indicate whether the parameters are statistically different from zero ($*$, $**$, $***$ correspond to significance at the 10%, 5%, and 1% level, respectively). The estimated slopes for hedgers and financial intermediaries

are highly statistically significant, with the latter demand curve being flatter. In tranquil times, intermediaries have the highest price elasticity and are the group most willing to take counterpositions. This ability shows how intermediaries facilitate hedging of producers and contribute to the functioning of the market. The slope parameter of others is not significant, potentially reflecting trader heterogeneity within this group.

To test Hypothesis 1, we evaluate $\mathcal{A}(2)$. The last column of this matrix contains the estimated changes in the slopes of the demand curves:

$$\mathcal{A}(2) = \begin{pmatrix} 0 & 0 & \underset{(0.28)}{-0.31} \\ 0 & 0 & \underset{(0.14)}{-1.26^{***}} \\ 0 & 0 & \underset{(0.60)}{0.41} \end{pmatrix}.$$

The only slope that changes significantly is the one for intermediaries. The change has the expected sign and is economically relevant. The demand curve steepens by more than 80%.

Adding $\bar{A}$ and $\mathcal{A}(2)$ yields the slope coefficients in state 2:

$$A(2) = \bar{A} + \mathcal{A}(2) = \begin{pmatrix} 1 & 0 & 1.06 \\ 0 & 1 & 1.52 \\ -1 & -1 & 0.56 \end{pmatrix} + \begin{pmatrix} 0 & 0 & -0.31 \\ 0 & 0 & -1.26 \\ 0 & 0 & 0.41 \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0.75 \\ 0 & 1 & 0.26 \\ -1 & -1 & 0.96 \end{pmatrix}.$$

We can now compare the slope for intermediaries $a^F(S_t)$ directly across regimes. The comparison shows that $a^F(1) = 1.52 > 0.26 = a^F(2)$, or, equivalently, that $a^F(2) - a^F(1) = -1.26 < 0$. As this difference is statistically different from zero the estimates suggest that intermediaries absorb trades of other market participants to a lesser extent during turbulent times.

This result lends support to the prediction of the theoretical literature that intermediary asset pricing is state-dependent, and shows that the oil futures market is a typical asset market. Moreover, together with the smoothed state probabilities it suggests that this market is not only affected by own developments but also by financial turmoil originating in other markets where financial intermediaries are active as well. Brunnermeier and Pedersen (2009) refer to this phenomenon as "commonality of liquidity across assets" which results from the difficulty of large banks to raise capital during periods of stress. As a result, market liquidity as a whole can decrease and observed price volatility increases.

To further judge the economic significance of the change in demand functions, we interpret the overall effects of net long demand shocks in both states. They take into

account all instantaneous feedback among positions and prices and are given by

$$A(1)^{-1} = \begin{pmatrix} 0.66 & -0.34 & -0.34 \\ -0.48 & 0.52 & -0.48 \\ 0.32 & 0.32 & 0.32 \end{pmatrix}, \qquad A(2)^{-1} = \begin{pmatrix} 0.62 & -0.38 & -0.38 \\ -0.13 & 0.87 & -0.13 \\ 0.51 & 0.51 & 0.51 \end{pmatrix}. \tag{12}$$

Each column shows the effects of a demand shock of a given trader group on the positions of hedgers and intermediaries, and on prices. Comparing the response of intermediaries' positions to demand shocks of the other two trader groups between state 1 and 2 shows that intermediaries absorb trades from other market participants to a lesser extent in the turbulent state. The respective value decreases in absolute terms from 0.48 to 0.13. Instead, intermediaries are mostly trading for own reasons, as indicated by the increase from 0.52 to 0.87 of the effect of their own shocks on own positions.

The bottom rows show that regardless of which trader groups' demand is shifting, the price impact in a given regime is the same as it depends on all traders' demand curves (see last rows in (4) and (12)). Across regimes, however, the price impact increases strongly, by nearly 60%. When interpreting this number, one has to bear in mind that the elements in $A(S)^{-1}$ are functions of all three estimated slopes in $A(S)$ and that some coefficients and their changes are not statistically significant. But when considering only the significant change in the coefficient for intermediaries, a^F, the price effect of demand shocks is 0.53, which is virtually the same as when considering all changes in slopes.[4] Hence, regardless of the precise computation, the price impact of any trade in the market increases by almost two thirds in state 2, and the results indicate that this is mostly due to a steeper demand curve of financial intermediaries.

To test Hypothesis 2, we turn to the estimated structural variances in state 1, $\Lambda(1)$, and their switch to state 2, $\tilde{\Lambda}(2)$:

$$\Lambda(1) = \bar{\Lambda} = \begin{pmatrix} \underset{(0.13)}{0.71^{***}} & 0 & 0 \\ 0 & \underset{(0.06)}{0.47^{***}} & 0 \\ 0 & 0 & \underset{(0.66)}{1.90^{***}} \end{pmatrix}, \qquad \tilde{\Lambda}(2) = \begin{pmatrix} \underset{(0.35)}{1.18^{***}} & 0 & 0 \\ 0 & \underset{(0.12)}{0.45^{***}} & 0 \\ 0 & 0 & \underset{(1.11)}{1.46} \end{pmatrix}.$$

In state 1, intermediaries have the smallest reaction to own shocks, if we interpret $\bar{\lambda}^F$ as the exposure to idiosyncratic balance sheet shocks. This finding is consistent with the idea that in normal times they can easily absorb ordinary balance sheet shocks. In state 2, however, the volatility of demand shifts of intermediaries almost doubles from

[4] In detail, the coefficients in the last row are given by $1/\tilde{a}(S_t)$, where $\tilde{a}(S_t) = a^H(S_t) + a^F(S_t) + a^O(S_t)$. Hence, $1/\tilde{a}(1) = 0.32$ and $1/\tilde{a}(2) = 0.51$. If we only change $a^F(S_t)$ between states, that is $\tilde{a}(2^*) = a^H(1) + a^F(2) + a^O(1)$, then we obtain $1/\tilde{a}(2^*) = 0.53$.

0.47 to 0.92. Importantly, the change $\lambda^F(2) - \lambda^F(1) = 0.45 > 0$ is statistically significant at the one percent level. The estimates thus support Hypothesis 2 and suggest that during turbulent times the exposure of financial intermediaries to shocks hitting their balance sheet increases. Finally, the volatility of demand shocks of hedgers also changes significantly across regimes, being already relatively high in state 1. This finding suggests that producers and processors of oil have a large exposure to oil market specific shocks already during normal times, consistent with many items on their balance sheet being linked to the price of oil. This sensitivity increases further during episodes that contain large oil price swings.

Putting the results together, we calculate the overall impact of the different demand shocks on the endogenous variables. Using $\Lambda(2) = \bar{\Lambda} + \tilde{\Lambda}(2)$, they are given by

$$A(1)^{-1}\Lambda(1)^{0.5} = \begin{pmatrix} 0.56 & -0.23 & -0.47 \\ -0.41 & 0.35 & -0.67 \\ 0.27 & 0.22 & 0.44 \end{pmatrix}, \quad A(2)^{-1}\Lambda(2)^{0.5} = \begin{pmatrix} 0.85 & -0.36 & -0.70 \\ -0.18 & 0.83 & -0.24 \\ 0.69 & 0.49 & 0.93 \end{pmatrix}.$$

The numbers resemble those in (12) but provide additional insights as they take into account the size of demand shifts. While in state 1 intermediaries' positions are more driven by trades of other market participants than by own needs, this drastically changes during state 2, where intermediaries change positions predominantly in response to own shocks. Moreover, when taking into account the larger variances in state 2, the increase in the price impact of all demand shocks across regimes is even more pronounced. The price effects more than double in all cases.

Finally, we compare different model specifications through Likelihood Ratio tests as another means of analyzing the statistical properties of the main results. We compare the log-likelihood of the just-identified baseline model, where the slope of the demand curve and the structural shock variance for intermediaries are, among other parameters, allowed to change across regimes, to three alternative over-identified model variants, where some of these parameters are assumed to be time-invariant. We set either $\alpha^F(2) = 0$ (see 6), $\ell^F(2) = 0$ (see 7), or impose both restrictions simultaneously, that is, $\alpha^F(2) = \ell^F(2) = 0$. Table 2 shows that in all three cases the p-values of the tests are essentially zero, clearly rejecting the restrictions. We conclude that a model which allows for fully state-dependent trading behavior of intermediaries is favored by the data.

Table 2: Likelihood Ratio Tests of Restrictions for the MSH-SVAR Model

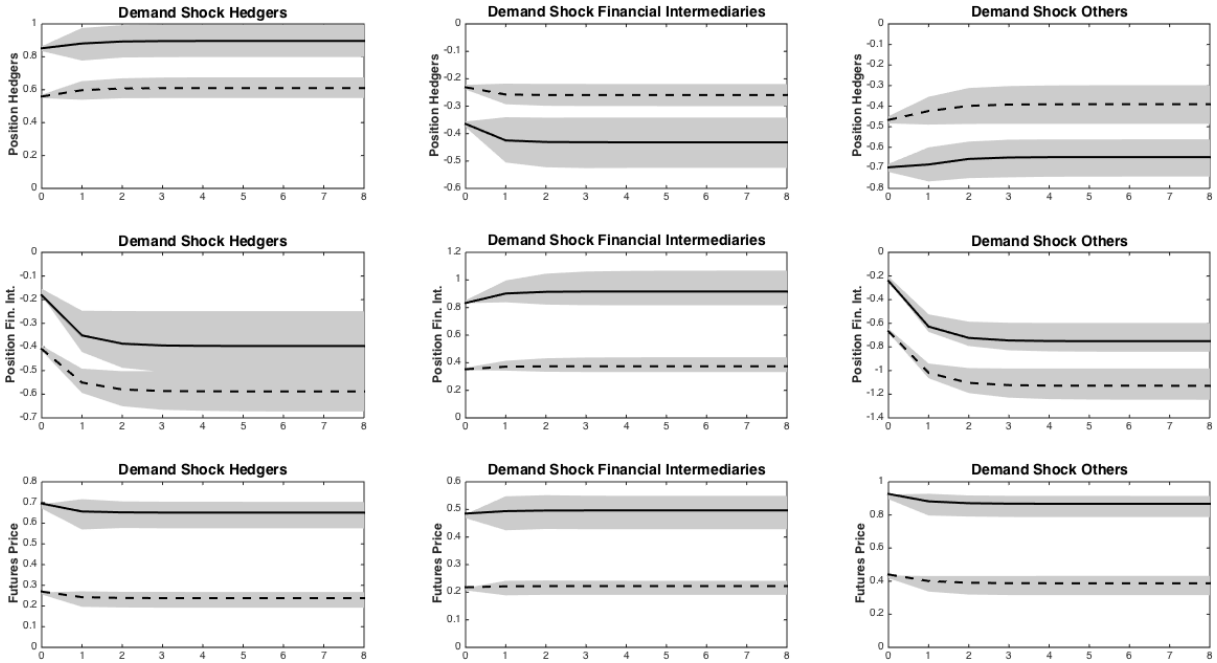
H_1: baseline model specification		
$H_0 : \alpha^F(2) = 0$	$H_0 : \ell^F(2) = 0$	$H_0 : \alpha^F(2) = \ell^F(2) = 0$
1.11E-16	2.13E-04	0

Note: Likelihood Ratio tests comparing the baseline model specification (unrestricted model) with different alternative specifications in which parameters corresponding to financial intermediaries are set to zero (restricted model). Numbers represent p-values of the null hypothesis.

3.4 Impulse Responses and Forecast Error Variances

The matrices discussed so far show differences in the impact effects of the shocks across states. We now present impulse responses to assess the dynamic effects. The bootstrapped confidence intervals also provide a further alternative of testing whether the effects are significantly different across regimes, both upon impact and subsequently. Figure 2 shows the cumulative responses in both states.[5] The dashed line refers to the tranquil state and the solid line to the turbulent state. The shaded area displays 90% confidence intervals based on 1000 bootstrap replications. Overall, the figure corroborates the conclusions based on the impact effects. All responses are significantly different across regimes. In particular, the price effects of all three types of demand shocks are significantly larger in state 2. Moreover, we again find that financial intermediaries react stronger to their own shocks during turbulent times while absorbing less of the other traders' demand shocks. In contrast, hedgers react more to intermediaries' demand.

Figure 2: Cumulative Impulse Responses with 90% Bootstrapped Confidence Intervals



Note: Comparison of cumulative impulse responses of the three endogenous variables (in rows) to the three demand shocks (in columns) in state 1 (dashed line) and state 2 (solid line). Shaded areas represent 90% confidence intervals based on 1000 bootstrapped replications using a fixed design wild bootstrap. Vertical axes are in absolute changes in case of position variables and percentage changes in case of the futures price, horizontal axes are in weeks.

The figure also shows that the largest effects occur on impact with only a limited role for the dynamics, in particular of prices. This observation is in line with asset prices and financial market participants responding instantaneously to each other, and has several

[5] The cumulative response for a given time horizon is the sum of all responses from the previous horizons until the current horizon. It therefore naturally stays persistent and is not expected to revert back to zero.

implications. First, it suggests that the estimates and the statistical inference based on the impact matrices capture quantitatively most of the nonlinear effects of intermediary asset pricing. Second, it implies that other empirical approaches that are based on lead/lag relationships between variables for the identification of the impact of trading behavior on asset prices, or vice versa, are likely to miss a relevant fraction of the overall effects. Finally, technically, it means that the underlying assumption of no regime change over the impulse horizon is not crucial as most of the difference between regimes is on impact. Moreover, this assumption seems plausible for the chosen horizon of eight weeks as Figure 1 indicates a high persistence of each state. In fact, the probability of staying in the current state is 0.96 for both states.

As a final means of quantifying the importance of state-dependencies we compute forecast error variance decompositions. They yield the average regime-specific contribution of the structural shocks to the variability of the endogenous variables. We focus on the contributions of the shocks on impact which are similar to the decompositions for longer horizons. Table 3 shows that during tranquil times less than a fifth of the variability of intermediaries' positions is explained by own shocks. They mainly respond to demand shocks of hedgers and other traders. This is in stark contrast to the turbulent state, where nearly 90% of the variation in intermediaries' position is explained by own shocks. Each of the other two shocks contributes only about 5%. Interestingly, the importance of intermediaries' demand shocks for price fluctuations remains constant across regimes at 15%, despite a significant increase in the volatility of their demand shocks in state 2. This finding suggests that the main distinguishing feature of intermediaries relative to the other two trader groups is the significant decline in their price elasticity, which does not apply to the other two groups, rather than the increase in demand volatility in turbulent times, which is common to all three groups (although the increase is not statistically significant for the residual trader group).

Table 3: Forecast Error Variance Decomposition

Variable	State	Demand Shock Hedgers	Demand Shock Fin.Int.	Demand Shock Others
Position Hedgers	1	0.54	0.09	0.37
	2	0.54	0.10	0.36
Position Financial Intermediaries	1	0.23	0.17	0.60
	2	0.04	0.88	0.07
Futures Price	1	0.23	0.15	0.62
	2	0.31	0.15	0.54

Note: Contribution of the three demand shocks to the forecast error variance of the endogenous variables upon impact in state 1 and state 2. The results change only marginally for longer horizons given that there is not much persistence in the first-differenced variables.

4 State Determination and Sensitivity Analysis

In this section, we first investigate whether combinations of variables can be associated with the regimes identified by the Markov switching model through logit regressions on the smoothed probabilities. Then, we conduct a series of robustness tests of the Markov switching model.

4.1 Regression Analysis of State Probabilities

We relate the smoothed probabilities of state 2 of the MSH-SVAR model to a number of model-external variables through logit regressions.[6] This analysis can add to the economic interpretation of the agnostically identified regimes and potentially allows inferring which other markets are relevant for the trading of intermediaries in the oil futures market.

Since the smoothed probability is a continuous measure, we transform it into a dichotomous variable by assigning 1 whenever it is above 0.5, and 0 otherwise. Only 16% of the observations have a probability between 0.10 and 0.90, supporting this transformation. As regressors, we include a constant and, as suggested by the MS process, one lag of the original state probability. Given the high autocorrelation of the smoothed probabilities, this lag transforms the model essentially into a specification in first differences. We therefore use first (log) differences of the other regressors as well, which also reduces the risk of spurious regression. The regressors are the log S&P 500 index, the ten-year U.S. Treasury rate, a trade weighted U.S. Dollar index and the log oil spot price.

Table 4 shows the point estimates for the different variables, adding them one-by-one. Robust standard errors are in parentheses. The log odds for each variable has the expected sign and five out of the seven variables are significant. Increases in the VIX or the Baa-Aaa corporate bond spread signal higher uncertainty and reflect widening credit spreads, which are both signs of financial market stress. Increases in the S&P 500, in the ten-year rate, and the oil spot price, on the other hand, lower the probability of state 2. Lower equity or oil returns have adverse effects on intermediaries' trading constraints.

In Table 5 we add the same variables sequentially to the model. Only two variables remain significant: the Baa-Aaa spread and the ten-year Treasury rate. The negative coefficient on the Treasury rate is consistent with "flight to quality" phenomena (Brunnermeier and Pedersen, 2009) in state 2, induced by a commonality of liquidity across asset markets and resulting in declining yields. Both coefficients are also in line with

[6] We choose a logit model for several reasons. First, standard OLS regressions seem inappropriate as the assumptions of linearity and homoskedasticity are violated. The smoothed probabilities show that many observations are close to 0 or 1, with only few observations with values in between. We opt for a logit model over a probit model as the former has fatter tails and is less sensitive to outliers. Probit regressions yield similar results, with the coefficients being smaller in absolute value as it is usually the case. Standard diagnostics tests like the link test for model adequacy or the Hosmer-Lemeshow test as well as inspecting the receiver operating characteristic curve indicate that the model is well specified.

Table 4: Logit Regressions Baseline Results

Regressor	VIX	Baa-Aaa spread	TED spread	Realized volatility	S&P 500	Ten-year rate	Exchange rate	Oil price
Coefficient	0.19***	13.05***	0.95	11.34	−0.22*	−6.54***	0.46	−0.14**
Robust S.E.	(0.07)	(4.86)	(1.46)	(12.96)	(0.11)	(1.68)	(0.30)	(0.06)

Note: Logit models with dependent variable equal to 1 if probability of state 2 of MSH-SVAR model $\geq$ 0.5, and 0 otherwise. Explanatory variables are in first differences and include a lag of the endogenous variable and a constant. Pseudo $R^2 = 0.90$ in all models. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively. Sample period: June 27, 2006 to May 24, 2016, weekly frequency, 517 observations. See Table 6 in Appendix A for a description of the variables.

Table 5: Logit Regressions Extended Models

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VIX	0.19***	0.17**	0.19**	0.18*	0.27*	0.24	0.23	0.23
	(0.07)	(0.07)	(0.08)	(0.09)	(0.16)	(0.18)	(0.16)	(0.15)
Baa-Aaa spread		11.15**	11.60**	12.39**	14.20**	12.71**	11.65**	10.61*
		(5.28)	(5.16)	(5.35)	(5.73)	(5.68)	(5.93)	(6.07)
TED spread			−1.84	−1.83	−2.17	−2.47	−1.56	−1.25
			(1.67)	(1.81)	(1.64)	(1.83)	(2.39)	(2.57)
Realized volatility				8.26	10.90	7.76	7.85	8.79
				(10.78)	(12.11)	(11.58)	(11.11)	(10.61)
S&P 500					0.15	0.25	0.29	0.32
					(0.23)	(0.21)	(0.20)	(0.19)
10y TB rate						−5.48**	−6.05***	−5.70***
						(2.30)	(2.13)	(2.07)
Exchange rate							0.29	0.20
							(0.29)	(0.30)
Oil price								−0.07
								(0.08)
Observations	517	517	517	517	517	517	517	517
Pseudo R^2	0.90	0.90	0.90	0.90	0.91	0.91	0.91	0.91

Note: Logit models with dependent variable equal to 1 if probability of state 2 of MSH-SVAR model $\geq$ 0.5, and 0 otherwise. Explanatory variables are in first differences and include a lag of the endogenous variable and a constant. Robust standard errors are in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively. Sample period: June 27, 2006 to May 24, 2016, weekly frequency. See Table 6 in Appendix A for a description of the variables.

risk premia and risk-free rates being important factors for the futures basis and hence for futures price dynamics (Acharya et al., 2013, Szymanowska et al., 2014). funding abilities of financial intermediaries who in turn become less willing and/or able to take over price risks form hedgers in the oil futures market.

4.2 Sensitivity Analysis

The section concludes with a number of robustness tests of the baseline MSH-SVAR model. First, we enlarge the baseline model by including another trader group, namely, the DCOT group of "Other Reportables." This group consists of reportable traders not classified as producers/processors/users, swap dealers, or money managers (see Appendix A). Second, as in Herwartz and Lütkepohl (2014), we allow for a third volatility state. Appendix B contains a figure with the smoothed probabilities for states 2 and 3. Third, we shorten the estimation period to June 12, 2007 until May 27, 2014 to exclude the large oil price swings at the beginning and end of the sample. Fourth, we allow for a more flexible specification with a switching intercept term. Fifth, we include all financial variables of

Table 5 except the oil spot price in first (log-)differences as exogenous control variables in the model. Sixth, we exclude all exogenous variables from the model. Seventh, we estimate a model with four lags. Eighth, we allow for predetermined exogenous variables. Ninth, instead of using the log-change in the oil futures price, we employ the change in the oil futures-spot basis as a third variable besides the two position variables.

Table 7 in Appendix B contains the key results of these alterations. They are qualitatively and mostly quantitatively similar to the baseline estimates, which are repeated in the first row for comparison. In all specifications the demand curve of financial intermediaries steepens significantly in the turbulent state, and the volatility of their own demand shocks is significantly larger. The endogenously identified states are similar across specifications and the correlation between the probability of state 2 in the baseline model and in alternative specifications is usually quite high (see second column).[7] Overall, the main results appear to be robust to the various alterations of the model and the data.

5 Conclusion

Modern asset pricing theories state that financial intermediaries face numerous frictions through which they affect the performance of financial markets. One of them is that during volatile times their trading constraints become binding and their risk-bearing capacity shrinks. Intermediaries may then be less able to enter new trades and may have to unwind existing positions. Such occasionally binding constraints lay the theoretical foundation for nonlinearities in the asset pricing of intermediaries (Brunnermeier and Pedersen, 2009, He and Krishnamurthy, 2013).

This paper contributes to the literature by taking a market microstructure view and providing direct structural estimates of the state-dependent trading behavior of intermediaries. We build a Markov switching in heteroskedasticity model for the oil futures market and test for the presence of nonlinearities, using weekly data for the period June 2006 until May 2016. The model contains two endogenously identified states, one corresponding to low and one to high volatility. The empirical results suggest two central nonlinearities. First, the downward-sloping demand curve of intermediaries steepens significantly in the high volatility regime. The lower price elasticity implies that intermediaries accommodate the hedging needs of producers, processors and consumers of oil to a lesser extent. This increases the price effect of these demand shocks strongly. Second, the volatility of intermediaries' own demand shocks increases significantly during these episodes. This raises futures price volatility further.

[7] One exception is the model with the futures basis, which is more volatile than the futures price. Further, the more volatile states 2 and 3 of the three-state model depict similar periods as state 2 in the baseline model, and would thus be jointly correlated with that state.

These findings indicate the existence and empirical relevance of the theoretically predicted state-dependency of intermediary asset pricing. Quantitatively, the estimates suggest that the steepening of the demand curve is the more important nonlinearity, and the main distinguishing feature of intermediaries relative to other trader groups in the oil futures market. Open questions are whether these nonlinearities are also present at lower frequencies, whether they help to explain the higher volatility of oil prices at high(er) frequencies, and how the microeconomic evidence generalizes to other markets.

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A Data Appendix

Table 6: Definition of Variables

Variable	**Definition and Source**
Position Hedgers	Net long position of the trader group "Producer/Merchant/Processor/User" in light sweet crude oil traded at the New York Mercantile Exchange. Standardized first absolute differences. U.S. Commodity Futures Trading Commission (CFTC), Disaggregated Commitments of Traders (DCOT) Report.
Position Financial Intermediaries	Net long position of the trader group "Swap Dealer" in light sweet crude oil traded at the New York Mercantile Exchange. Standardized first absolute differences. U.S. Commodity Futures Trading Commission (CFTC), Disaggregated Commitments of Traders (DCOT) Report.
Futures Price	New York Mercantile Exchange light crude oil continuous futures settlement price. Standardized first log-differences. Datastream. Series code: NCLCS00. It is the front contract continuous time series, which uses the price of the most current contract and pricing automatically rolls over when the contract expires.
Initial Jobless Claims	Number Initial Claims, Weekly, Ending Saturday, Seasonally Adjusted. Standardized first log-differences. Federal Reserve Economic Data, St. Louis Fed. Series code: ICSA.
Fed Total Assets	All Federal Reserve Banks Total Assets, Millions of Dollars, Weekly, as of Wednesday, Not Seasonally Adjusted. Standardized first log-differences. Federal Reserve Economic Data, St. Louis Fed. Series code: WALCL.

U.S. Macroeconomic Surprise Indicators	Difference between actual release and the median forecast estimate of economists surveyed by Bloomberg. Indicators: American Consumer Spending Growth Rates MoM SA (PCE CRCH:IND), Average Hourly Earnings MoM% SA (AHE MOM%:IND), Average Hourly Earnings YoY% SA (AHE YOY%:IND), Business Inventories MoM SA (MTIBCHNG:IND), Capacity Utilization % of Total Capacity (CPTICHNG:IND), Conference Board Leading Indicators MoM (LEI CHNG:IND), Construction Spending Total MoM SA (CNSTTMOM:IND), Core Producer Price Index (PPI XYOY:IND), CPI Urban Consumers Less Food & Energy YoY NSA (CPI XYOY:IND), CPI Urban Consumers MoM SA (CPI CHNG:IND), CPI Urban Consumers YoY NSA (CPI YOY:IND), Durable Goods New Orders Industries MoM SA (DGNOCHNG:IND), GDP Chained 2009 Dollars QoQ SAAR (GDP CQOQ:IND), Housing Starts/Permits (NHSPSTOT:IND), Industrial Production MoM 2007=100 SA (IP CHNG:IND), Initial Jobless Claims SA (INJCJC:IND), Markit Manufacturing PMI SA (MPMIUSMA:IND), Markit Services PMI Business Activity SA (MPMIUSSA:IND), Nonfarm Payrolls Total MoM SA (NFP TCH:IND), Personal Consumption Expenditure CPI YoY SA (PCE CYOY:IND), Personal Income MoM SA (PITLCHNG:IND), PPI Final Demand MoM SA (PCE CYOY:IND), PPI Finished Goods SA MoM% (PPI CHNG:IND), Producer Price Index - Finished Goods (PPI YOY:IND), Productivity Output Per Hour Nonfarm Business Sector QoQ SA (PRODNFR%:IND), Retail Sales (Less Auto and Gas Stations) SA MoM% Change (RSTAXAG%:IND), Trade Balance of Goods and Services SA (USTBTOT:IND), Unit Labor Costs Nonfarm Business Sector QoQ% SAAR (COSTNFR%:IND), University of Michigan Consumer Confidence Indicator (CONSSENT:IND), US Government Budget Balance FED (FDDSSD:IND)
10y TB rate	10 Year U.S. Treasury Benchmark Bond Redemption Yield, Weekly, Ending Tuesday. First absolute differences. Datastream. Series code: USBDS10Y.
Baa-Aaa spread	Difference between Moody's Seasoned Baa Corporate Bond Yield ©, Percent, Weekly, Ending Tuesday, Not Seasonally Adjusted and Moody's Seasoned Aaa Corporate Bond Yield ©, Percent, Weekly, Ending Tuesday, Not Seasonally Adjusted. First absolute difference. Federal Reserve Economic Data, St. Louis Fed. Series codes: DBAA and DAAA, respectively.
Exchange rate	Trade Weighted U.S. Dollar Index: Major Currencies, Index 27.06.2006 = 100, Weekly, Ending Tuesday. First log-differences. Federal Reserve Economic Data, St. Louis Fed. Series code: DTWEXM.
Oil price	Crude Oil Prices: West Texas Intermediate (WTI) - Cushing, Oklahoma, Dollars per Barrel, Weekly, Ending Tuesday, End of Period. First log-differences. Federal Reserve Economic Data, St. Louis Fed. Series code: DCOILWTICO.
Realized volatility	Square root of the weekly realized variance of the oil spot price, which is given by $RV_t = \sum_{j=1}^{n}(p_{t-1+\frac{j}{n}} - p_{t-1+\frac{j-1}{n}})^2$, where p_t denotes the logarithm of the oil spot price and n is the number of trading days during week t. First absolute differences. Source of the oil price see above.
S&P 500	Standard & Poor's 500 Stock Market Index, Weekly, Ending Tuesday. First log-differences (that is, the return). Yahoo Finance.
TED spread	TED Spread, Weekly, Ending Tuesday, End of Period. First absolute difference. Federal Reserve Economic Data, St. Louis Fed. Series code: TEDRATE.
VIX	CBOE Volatility Index: VIX, Weekly, Ending Tuesday, End of Period. First absolute difference. Federal Reserve Economic Data, St. Louis Fed. Series code: VIXCLS.

Definitions of Trader Groups in DCOT Reports

Below are the definitions of the four trader groups in the DCOT Reports as stated in CFTC (2017a). The fifth group of "Non-Reportables" is a residual component.

Producer/Merchant/Processor/User: An entity that predominantly engages in the production, processing, packing or handling of a physical commodity and uses the futures markets to manage or hedge risks associated with those activities.

Swap Dealer: An entity that deals primarily in swaps for a commodity and uses the futures markets to manage or hedge the risk associated with those swaps transactions. The swap dealer's counterparties may be speculative traders, like hedge funds, or traditional commercial clients that are managing risk arising from their dealings in the physical commodity.

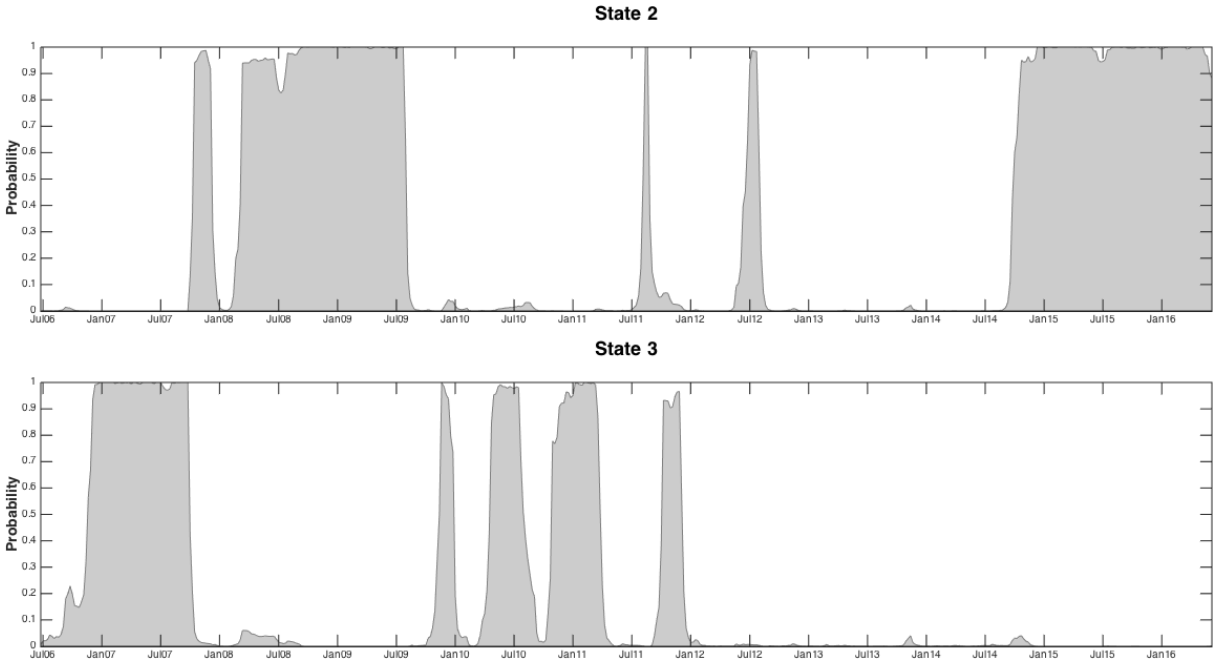
Money Manager: A registered commodity trading advisor (CTA); a registered commodity pool operator (CPO); or an unregistered fund identified by CFTC. These traders are engaged in managing and conducting organized futures trading on behalf of clients.

Other Reportables: Every other reportable trader that is not placed into one of the other three categories is placed into the "other reportables" category.

Non-Reportables: The remainder of total open interest in the specific futures market that is not accounted for by the other four categories of traders.

B Sensitivity Analysis: Additional Figure and Table

Figure 3: Smoothed Probabilities of the Two Volatile States in the Robustness Check



Note: Plot of the endogenously estimated smoothed probabilities of the two high volatility states, that is, the "turbulent states," in the robustness check of the baseline model with three different states.

Table 7: Sensitivity Analysis

Alternative specification	$\rho\left(S_t(2)^{base.}, S_t(2)^{alt.}\right)$	$A(1) = \bar{A}$	$\mathcal{A}(2)$	$\Lambda(1) = \bar{\Lambda}$	$\bar{\Lambda}(2)$
Baseline model	1.00	$\begin{pmatrix} 1 & 0 & 1.06^{***} \\ 0 & 1 & 1.52^{***} \\ -1 & -1 & 0.56 \end{pmatrix}$	$\begin{pmatrix} 0 & 0 & -0.31 \\ 0 & 0 & -1.26^{***} \\ 0 & 0 & 0.41 \end{pmatrix}$	$\begin{pmatrix} 0.71^{***} & 0 & 0 \\ 0 & 0.47^{***} & 0 \\ 0 & 0 & 1.90^{***} \end{pmatrix}$	$\begin{pmatrix} 1.18^{***} & 0 & 0 \\ 0 & 0.45^{***} & 0 \\ 0 & 0 & 1.46 \end{pmatrix}$
Additional trader group	0.89	$\begin{pmatrix} 1 & 0 & 0 & 1.07^{***} \\ 0 & 1 & 0 & 1.28^{***} \\ 0 & 0 & 1 & 1.40^{***} \\ -1 & -1 & -1 & -0.25 \end{pmatrix}$	$\begin{pmatrix} 0 & 0 & 0 & -0.56^{***} \\ 0 & 0 & 0 & -1.10^{***} \\ 0 & 0 & 0 & -1.08^{***} \\ 0 & 0 & 0 & 1.45^{***} \end{pmatrix}$	$\begin{pmatrix} 0.80^{***} & 0 & 0 & 0 \\ 0 & 0.57^{***} & 0 & 0 \\ 0 & 0 & 0.79^{***} & 0 \\ 0 & 0 & 0 & 2.17^{***} \end{pmatrix}$	$\begin{pmatrix} 0.75^{***} & 0 & 0 & 0 \\ 0 & 0.26^{**} & 0 & 0 \\ 0 & 0 & 0.28^{*} & 0 \\ 0 & 0 & 0 & 2.85^{*} \end{pmatrix}$
Three states: State 2	0.71	$\begin{pmatrix} 1 & 0 & 0.85^{***} \\ 0 & 1 & 1.50^{***} \\ -1 & -1 & 0.94 \end{pmatrix}$	$\mathcal{A}(2) = \begin{pmatrix} 0 & 0 & -0.76^{***} \\ 0 & 0 & -1.37^{***} \\ 0 & 0 & 1.99 \end{pmatrix}$	$\begin{pmatrix} 0.62^{***} & 0 & 0 \\ 0 & 0.42^{***} & 0 \\ 0 & 0 & 2.43^{**} \end{pmatrix}$	$\Lambda(2) = \begin{pmatrix} 0.10 & 0 & 0 \\ 0 & 0.30^{***} & 0 \\ 0 & 0 & 15.67 \end{pmatrix}$
Three states: State 3	0.32		$\mathcal{A}(3) = \begin{pmatrix} 0 & 0 & 1.90^{***} \\ 0 & 0 & -1.35^{***} \\ 0 & 0 & -0.74 \end{pmatrix}$		$\Lambda(3) = \begin{pmatrix} 3.26^{**} & 0 & 0 \\ 0 & 0.57^{***} & 0 \\ 0 & 0 & -0.22 \end{pmatrix}$
Shorter sample period: June 12, 2007 to May 27, 2014	0.94	$\begin{pmatrix} 1 & 0 & 0.79^{***} \\ 0 & 1 & 1.61^{***} \\ -1 & -1 & 0.63 \end{pmatrix}$	$\begin{pmatrix} 0 & 0 & 0.25 \\ 0 & 0 & -1.31^{***} \\ 0 & 0 & -0.11 \end{pmatrix}$	$\begin{pmatrix} 0.56^{***} & 0 & 0 \\ 0 & 0.41^{***} & 0 \\ 0 & 0 & 2.15^{**} \end{pmatrix}$	$\begin{pmatrix} 2.06^{***} & 0 & 0 \\ 0 & 0.32^{***} & 0 \\ 0 & 0 & 0.15 \end{pmatrix}$
Switching intercept	0.99	$\begin{pmatrix} 1 & 0 & 1.06^{***} \\ 0 & 1 & 1.51^{***} \\ -1 & -1 & 0.50 \end{pmatrix}$	$\begin{pmatrix} 0 & 0 & -0.33 \\ 0 & 0 & -1.27^{***} \\ 0 & 0 & 0.50 \end{pmatrix}$	$\begin{pmatrix} 0.71^{***} & 0 & 0 \\ 0 & 0.47^{***} & 0 \\ 0 & 0 & 1.85^{***} \end{pmatrix}$	$\begin{pmatrix} 1.12^{***} & 0 & 0 \\ 0 & 0.42^{***} & 0 \\ 0 & 0 & 1.63 \end{pmatrix}$
Additional exogenous variables	0.88	$\begin{pmatrix} 1 & 0 & 1.00^{***} \\ 0 & 1 & 1.33^{***} \\ -1 & -1 & 1.71^{*} \end{pmatrix}$	$\begin{pmatrix} 0 & 0 & -0.03 \\ 0 & 0 & -1.09^{***} \\ 0 & 0 & -0.57 \end{pmatrix}$	$\begin{pmatrix} 0.61^{***} & 0 & 0 \\ 0 & 0.47^{***} & 0 \\ 0 & 0 & 2.90^{**} \end{pmatrix}$	$\begin{pmatrix} 1.67^{***} & 0 & 0 \\ 0 & 0.55^{***} & 0 \\ 0 & 0 & 0.09 \end{pmatrix}$
No exogenous variables	0.89	$\begin{pmatrix} 1 & 0 & 0.99^{***} \\ 0 & 1 & 1.29^{***} \\ -1 & -1 & 0.62^{*} \end{pmatrix}$	$\begin{pmatrix} 0 & 0 & -0.35 \\ 0 & 0 & -1.02^{***} \\ 0 & 0 & -0.50 \end{pmatrix}$	$\begin{pmatrix} 0.80^{***} & 0 & 0 \\ 0 & 0.62^{***} & 0 \\ 0 & 0 & 2.05^{***} \end{pmatrix}$	$\begin{pmatrix} 1.17^{***} & 0 & 0 \\ 0 & 0.44^{***} & 0 \\ 0 & 0 & 2.67 \end{pmatrix}$
Four lags of the endogenous variables	0.94	$\begin{pmatrix} 1 & 0 & 0.76^{***} \\ 0 & 1 & 1.48^{***} \\ -1 & -1 & 0.94 \end{pmatrix}$	$\begin{pmatrix} 0 & 0 & 0.07 \\ 0 & 0 & -1.23^{***} \\ 0 & 0 & 0.03 \end{pmatrix}$	$\begin{pmatrix} 0.51^{***} & 0 & 0 \\ 0 & 0.40^{***} & 0 \\ 0 & 0 & 2.34^{**} \end{pmatrix}$	$\begin{pmatrix} 1.43^{***} & 0 & 0 \\ 0 & 0.48^{***} & 0 \\ 0 & 0 & 1.08 \end{pmatrix}$
Predetermined exogenous variables	0.89	$\begin{pmatrix} 1 & 0 & 0.65^{***} \\ 0 & 1 & 1.25^{***} \\ -1 & -1 & 2.15 \end{pmatrix}$	$\begin{pmatrix} 0 & 0 & 0.31 \\ 0 & 0 & -0.97^{***} \\ 0 & 0 & -1.35 \end{pmatrix}$	$\begin{pmatrix} 0.46^{***} & 0 & 0 \\ 0 & 0.36^{***} & 0 \\ 0 & 0 & 4.53 \end{pmatrix}$	$\begin{pmatrix} 1.76^{***} & 0 & 0 \\ 0 & 0.59^{***} & 0 \\ 0 & 0 & -1.83 \end{pmatrix}$
Futures basis instead of futures price	0.26	$\begin{pmatrix} 1 & 0 & 1.28^{***} \\ 0 & 1 & 1.44^{***} \\ -1 & -1 & 11.70^{***} \end{pmatrix}$	$\begin{pmatrix} 0 & 0 & -0.98^{**} \\ 0 & 0 & -1.11^{***} \\ 0 & 0 & -11.14^{***} \end{pmatrix}$	$\begin{pmatrix} 0.93^{***} & 0 & 0 \\ 0 & 0.84^{***} & 0 \\ 0 & 0 & 8.70^{*} \end{pmatrix}$	$\begin{pmatrix} 1.48^{*} & 0 & 0 \\ 0 & 0.51 & 0 \\ 0 & 0 & -5.87 \end{pmatrix}$

Note: The table reports the main results of the following robustness tests: a model including a third trader group (the DCOT group "Others"), a model with three states, a model encompassing a shorter sample period, a model featuring a switching intercept, a model with additional exogenous variables and one without any exogenous variables, a model with four lags of the endogenous variables, a model which allows for predetermined exogenous variables, and a model in which the futures basis is used instead of the futures price. The first row contains the results for the baseline model. The second column states the correlation between the turbulent state of the baseline model and the alternative model (in case of the three-state model among the turbulent state of the baseline model and both volatile states of the alternative model). The remaining columns display the matrix A of instantaneous relations among the endogenous variables and its switch $\mathcal{A}(2)$ to the turbulent state ($\mathcal{A}(2)$ and $\mathcal{A}(3)$ in case of the three-state model), as well as the variances of the identified demand shocks $\Lambda(1)$ and their switch $\Lambda(2)$ to the turbulent state ($\Lambda(2)$ and $\Lambda(3)$ in case of the three-state model). *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively. The full set of results is available upon request.