Three essays on benchmarks, derivatives, and OTC markets

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BY
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To the people I love, who have encouraged and supported me—always.

Three essays on benchmarks, derivatives, and OTC markets

Extended abstract

Thesis advisors: Professor Alex Frino
Associate Professor Gbenga Ibikunle
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by Tom Steffen

This dissertation consists of three empirical studies. Collectively, the chapters cover over-the-counter (OTC) markets and assess the interactions with centralized exchange-traded markets via benchmarks and financial derivatives.

Chapter 1, "The impact of commodity benchmarks on derivatives markets: The case of the Dated Brent assessment and Brent futures", examines the response of the futures market to the key spot oil benchmark assessed and published by Platts. Futures trading activity intensifies during the assessment window and aligns with the direction of the upcoming benchmark publication. A substantially increased arrival rate of informed traders suggests that sophisticated traders induce the futures price run-up ahead of the Dated Brent assessment ending point. The general increase in the arrival rates of both informed and uninformed traders during the assessment window underscores the benchmark's significance as a critical financial market infrastructure element.

Chapter 2, "*Skin in the game*: Resource proximity and price impact", exploits a novel dataset incorporating OTC oil forward trading with exchange-traded futures activity to investigate the intricate interactions between both markets. I confirm that the futures market is the uncontested information leader, but that the forward market contributes a non-negligible proportion to the determination of the efficient oil price. Further, I find that fundamental supply and demand information, likely gained through 'skin in the game' in upstream and downstream oil infrastructure, proxied by the traders' centrality in the forward market, is revealed to the futures market by their forward trading activity.

Chapter 3, "The visible hand: Benchmarks, regulation, and liquidity", suggests that a more precise assessment of the OTC interest rate swap benchmark can enhance welfare by improving the traders' ability to monitor the dealers. The transition from the unregulated submission-based ISDAFIX regime to the more transparent and regulated market-based ICE Swap Rate regime provides a natural experiment for testing this proposition empirically. Utilizing proprietary electronic order book data for USD interest rate swaps, I confirm that liquidity in the underlying swaps, affected by the regime switch, improves significantly more vis-à-vis swaps not impacted by the change in assessment procedure.

Adapted papers

I, Tom Steffen*, am the author of all chapters, and the research contained in this thesis is the product of my own original effort (with the exception of Section II, Chapter 3). Several chapters have been developed into co-authored papers, as detailed below.

- *Chapter 1* resulted in the following peer-reviewed publication:

  "The impact of commodity benchmarks on derivatives markets: The case of the Dated Brent assessment and Brent futures", (with Alex Frino†, Gbenga Ibikunle‡, Vito Mollica§), *Journal of Banking & Finance*, forthcoming, https://doi.org/10.1016/j.jbankfin.2017.08.017.

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- *Chapter 2* is available as a working paper:

  "*Skin in the game*: Resource proximity and price impact", Working Paper, 2018, University of Edinburgh and Macquarie University.

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- *Chapter 3* resulted in the following publication:

  "Benchmark regulation and market quality", (with Matteo Aquilina[¶], Gbenga Ibikunle, Vito Mollica), FCA Occasional Paper No. 27, 2017, Financial Conduct Authority, https://www.fca.org.uk/publications/occasional-papers/no-27-benchmark-regulation-market-quality.

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Statement of originality

I, Tom Steffen, declare that this thesis titled, *Three essays on benchmarks, derivatives, and OTC markets*, and the work presented in it has not previously been submitted for a degree or diploma in any university. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

Tom Steffen	9 August 2018
Signed	Date

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Acronyms

A | B | C | D | E | F | G | H | I | L | M | N | O | P | Q | R | S | T | U | V | W | Y

A

AIC Akaike information criterion.
am Ante meridiem.

B

bbl Barrel.
BBO Best bid and offer.
BFO Brent-Forties-Oseberg.
BFOE Brent-Forties-Oseberg-Ekofisk.
BGC Partners Bernard Gerald Cantor Partners.
BIS Bank for International Settlements.
BMD Benchmark-to-market differential.
BMR EU Benchmarks Regulation.
BoE Bank of England.
BP Bai and Perron.
bps Basis points.
BRC Benchmark regime change.
BST British Summer Time.

C

CDR Cumulative directional returns.
CDS Credit default swap.
CEA Commodity Exchange Act.
CEO Chief executive officer.
CFD Contract for Differences.
CFTC Commodity Futures Trading Commission.
CLOB Central limit order book.
CMCRC Capital Markets Cooperative Research Centre.
CME Chicago Mercantile Exchange.
CP Consultation paper.
CS Component share.
CSR Cumulative simple returns.
CT Central Time.

D

DiD Difference-in-difference.
DOIB# Directional order imbalance by number of trades.
DR Directional returns.
DV Dependent variable.

E

ECB European Central Bank.
ECDF Empirical cumulative distribution function.
EFP Exchange of Futures for Physical.
EFTA European Free Trade Association.
EIA Energy Information Administration.
EL Ederington and Lee.

EL30# Ederington-and-Lee-corrected directional order imbalance by number of trades.
EL30R Ederington-and-Lee-corrected 30-minute directional returns.
EMIR European Market Infrastructure Regulation.
ESMA European Securities and Markets Authority.
ET Exchange-traded.
ET (time) Eastern Time.
ETF Exchange-traded fund.
EU European Union.
EUR Euro.
EURIBOR Euro Interbank Offered Rate.

F

FCA Financial Conduct Authority.
FICC Fixed income, currencies, and commodities.
FIXDIR Fixing direction.
FOMC Federal Open Market Committee.
FOW Forward.
FS Fill spread.
FTSE Financial Times Stock Exchange.
FUT Futures.
FX or FOREX Foreign exchange.

G

GARCH Generalized autoregressive conditional heteroskedasticity.
GBP Great Britain Pound.
GMT Greenwich Mean Time.

H

HMT Her Majesty's Treasury.

I

IBA ICE Benchmark Administration.
ICAP Intercapital plc.
ICE Intercontinental Exchange.
ICIS Independent Chemical Information Service.
IDB Inter-dealer broker.
IFEU ICE Futures Europe.
ILS Information leadership share.
IOSCO International Organization of Securities Commissions.
IRS Interest rate swap.
IS Information share.
ISDA International Swaps and Derivatives Association.

L

LBMA London Bullion Market Association.
LCH London Clearing House.
LE Liquidity effect.
LIBOR London Interbank Offered Rate.
LOB Limit order book.

M

MAR Market Abuse Regulation.
MAT Made available to trade.
MiFID Markets in Financial Instruments Directive.
MiFIR Markets in Financial Instruments Regulation.
MOC Market on Close.
MTF Multilateral trading facility.

N

NBER National Bureau of Economic Research.
NYMEX New York Mercantile Exchange.
NYSE New York Stock Exchange.

O

OLS Ordinary least squares.
OPIS Oil Price Information Service.
OTC Over-the-counter.

P

PE Permanent effect.
PGA Platts Global Alert.
PIN Probability of informed trade.
pm Post meridiem.
PRA Price reporting agency.

Q

QD Quoted depth.
QD10 10-level quoted depth.
QS Quoted spread.

R

RBA Reserve Bank of Australia.
RFQ Request for quote.
RM Regulated market.
RONIA Repurchase Overnight Index Average.
RQS Relative quoted spread.

S

S&P Standard & Poor's.
SEF Swap execution facility.
SFI Swiss Finance Institute.
SIRCA Securities Industry Research Centre of Asia-Pacific.
SMS Standard market size.
SNA Social network analysis.
SONIA Sterling Overnight Index Average.
SPDR Spider (a family of ETFs).
SR Simple returns.

T

TE Total effect.
TP Tullett Prebon.
TRACE Transaction Reporting and Compliance Engine.
TRTH Thomson Reuters Tick History.
TW Time-weighted.
TWFS Time-weighted fill spread.
TWLM Time-weighted liquidity measure.
TWQD Time-weighted quoted depth.
TWQD10 Time-weighted 10-level quoted depth.
TWQS Time-weighted quoted spread.
TWRQS Time-weighted relative quoted spread.

U

UK United Kingdom.
US United States.
USD United States Dollars.

V

V Volatility.
VECM Vector error correction model.
VIX Volatility index.
VM Volume.
VMA Vector moving average.

W

WM WM Company.
WTI West Texas Intermediate.

Y

Y Year.

Glossary

A | B | C | D | E | F | H | I | L | M | N | O | P | Q | R | S | T | U | V

A

Ask The price at which a seller is prepared to sell an asset.

B

Barrel A volumetric unit of measure for crude oil and petroleum products. 1 barrel is 42 US gallons, 35 imperial gallons or 159 liters. There are roughly 7.33 bbl of crude oil to a tonne, but the precise conversion obviously depends on the specific gravity of the oil (as defined by Platts, n.d.a).

Benchmark A benchmark as defined in Section 22(1A)(b) of the Act and specified in Schedule 5 to the Regulated Activities Order pursuant to article 63R of the Regulated Activities Order (defined by FCA, n.d.).

Benchmark administrator A person who has authorization to carry on the regulated activity of administering a specified benchmark (defined by FCA, n.d.).

Benchmark submitter A person carrying out the regulated activity of providing information in relation to a specified benchmark (defined by FCA, n.d.). In the context of this dissertation, a submitter is also a market participant whose trading activities contribute to the assessment of an unregulated benchmark.

Best The most advantageous price.

Bid The price at which a buyer is prepared to buy an asset.

Brent complex Physical and financial oil contracts related to North Sea crude oil, including, but not limited to, futures, forwards, cargoes, CFDs, and EFPs.

Brent or Brent blend The most commonly traded North Sea crude oil. [...] The blend is technically a mix of crude from the Shell UK-operated Brent field and the BP-operated Ninian field. The blend is, however, commonly referred to simply as Brent (defined by Platts, n.d.a).

Broker An intermediary between traders for physical, futures, and OTC transactions [...] (defined by InfoproDigital, n.d.). A broker acts on behalf of clients and charges a commission.

Butterfly A packaged trade involving the simultaneous trading of three different swap tenors on the swap curve (adapted from ClarusFT, n.d.).

C

Cargo In the context of this dissertation, a full cargo corresponds to 600,000 barrels and a partial cargo to 100,000 barrels.

Cash market The physical market underlying a futures or options contract (defined by Platts, n.d.a).

Cash settlement The settlement of futures or options by paying a cash difference, rather than taking/making physical delivery (defined by Platts, n.d.a).

Cleared swap Any swap that is directly or indirectly submitted to be cleared by a derivatives clearing organization registered either with the CFTC in the US or ESMA in Europe (defined by InfoproDigital, n.d.).

Clearing The process of matching trades, settling trades, and providing a guarantee for traded contracts, often a service performed by exchanges (defined by Platts, n.d.a). Clearing is being mandated for many types of OTC derivatives by rules [...] such as the Dodd-Frank Act [...] and EMIR (defined by InfoproDigital, n.d.).

Commodity A physical good that can be the object of a commercial transaction [...] or price determinant of a futures contract or other financial instrument (defined by InfoproDigital, n.d.).

Commodity trader A commodity trader focuses on investing in physical substances like oil [...]. Most often these traders are dealing in raw materials used at the beginning of the production value chain [...] (defined by Investopedia, n.d.a).

Contract for Differences Crude oil swap, tied to published price assessments, which exchanges floating short-term risk for fixed risk (defined by Platts, n.d.a).

Contract month Refers to one of the maturities on the forward (or futures) curve and is defined as the month in which the contract matures. The contract can then be settled. See also forward price curve.

Counterparty A principal participant in a physical or financial contract (defined by InfoproDigital, n.d.).

Curve trade A package involving the simultaneous trading of two different swap tenors on the swap curve (adapted from ClarusFT, n.d.).

D

Dated Brent Brent cargoes are known as dated Brent cargoes once they acquire a specific set of loading dates [...]. The dated Brent market [...] generates prices which have become a key benchmark for contract pricing of crude oil worldwide (defined by Platts, n.d.a). See also Dated Brent benchmark.

Dated Brent benchmark The Dated Brent benchmark is the leading crude oil reference price and is derived from the activity in the physical North Sea crude oil market. Platts computes the benchmark on a daily basis.

Dealer A market participant who takes part in a transaction as a principal. The dealer trades on his account, buying from or selling to clients, thereby often holding an inventory. A dealer profits from the spread between his bid and ask prices as well as the performance of his position.

Derivative A financial transaction that derives its value from the value of another asset. Commodity derivatives derive their value from physical commodity transactions. The value of a derivative rises and falls in accordance with the value of the underlying asset. Derivatives can be traded on regulated exchange markets or OTC (defined by Platts, n.d.a).

Dodd-Frank Act The Dodd-Frank Wall Street Reform and Consumer Protection Act is a legislative package introduced in the US in the aftermath of the financial crisis to decrease the risk in the financial system (adapted from InfoproDigital, n.d.).

Downstream Activities in the oil [...] industry from a refinery onwards—for example, the distribution and marketing of hydrocarbon products (defined by InfoproDigital, n.d.).

E

EU Benchmarks Regulation The EU Benchmarks Regulation imposed new requirements on firms that administer indexes and reference prices, or contribute inputs to them. The rules were [...] implemented across the EU on January 1, 2018 (defined by InfoproDigital, n.d.).

eWindow Platts Editorial Window (eWindow), an online data-entry and communications tool, [...] facilitates the price formation process by combining Platts' MOC price assessment methodology with state-of-the-art technology [...] licensed from ICE. [...] eWindow provides a clear view of all bids, offers, and transaction data communicated to Platts editors during the MOC price assessment process. It also allows participants [...] to directly submit and confirm deal information to Platts and the marketplace simultaneously (defined by Platts, n.d.b).

Exchange of Futures for Physical Refers to the exchange of a futures position for a physical [...] position (defined by Platts, n.d.a).

Exchange-traded Used to describe transactions that are concluded via a traditional and centralized exchange.

F

Forward contract An OTC transaction between two companies involving the future delivery of a commodity at a specific date and location at a fixed price [...]. Similar to a futures contract, but forwards can be customized to suit the specific needs of the counterparties involved while a futures contract is standardized and traded on an exchange (defined by Platts, n.d.a).

Forward price curve When plotted together, a series of forward prices creates a forward curve, reflecting a range of today's tradable values for specified dates in the future (defined by Platts, n.d.a).

Front month The closest-to-maturity forward (or futures) contract, which is maturing/expiring next.

Futures contract An exchange-traded transaction involving the future delivery of a commodity at a specific date and price. See also forward contract.

H

Hedging The opposite of speculation. The hedger holds an offsetting position to neutralize risk.

I

ICE Brent Crude futures ICE Futures Europe's most actively traded North Sea oil futures contract.

ICE Brent Index The index is administered by ICE Futures Europe and represents the average trading price in the relevant month of the BFOE forward market. The ICE Brent Index is published monthly and used for the cash settlement of ICE's futures contract—the ICE Brent Crude futures.

ICE Swap Rate The reformed global benchmark for the fixed leg price of fixed-for-floating IRS (formerly ISDAFIX) assessed by IBA.

Implied order An *Implied In* price is generated by the differential of two contracts. The differential of the known values (the legs) goes into generating the unknown value (the spread) (defined by TT, n.d.a). When calculating *Implied Outs*, a leg price is generated by the spread price and one of the legs. The differential of the known values (the spread price and a leg price) goes into generating the unknown value (a leg price) (defined by TT, n.d.b).

Index A numerical value assigned to a group of commodities, stocks, or prices in order to give an indication of market trends (defined by InfoproDigital, n.d.).

Inter-dealer broker Classification of a broker that traditionally organizes trading of cash and derivatives between wholesale dealers (defined by ClarusFT, n.d.).

Interest rate swap Describes an agreement between two counterparties in which one stream of future interest payments is exchanged for another based on a specified principal amount. Interest rate swaps usually involve the exchange of a fixed interest rate for a floating rate, or vice versa (adapted from Investopedia, n.d.b).

ISDAFIX The leading benchmark for fixed rates on fixed-for-floating IRS, established by ISDA until the end of March 2015. In April 2015, the benchmark was restructured by IBA and renamed to ICE Swap Rate.

L

Last The most recent price.

Leg A leg is one element of a swap, structured to exchange fixed payments (the fixed leg) and floating payments (the floating leg). Alternatively, the individual swap tenors in a packaged trade are referred to as legs too.

Liquidity The level of an asset's trading activity, or the ability to quickly buy or sell an asset in the market without affecting the price of that asset.

Long position A position that appreciates in value if the value of the underlying instrument [...] increases (defined by InfoproDigital, n.d.).

Lot The unit size for transactions on a given futures exchange (defined by InfoproDigital, n.d.).

M

Made available to trade A designation for swaps such that they become a Required Transaction under the CFTC Trade Execution Requirement. Such swaps are mandatory to be executed on SEFs (defined by ClarusFT, n.d.).

Market maker In the context of this dissertation, the term is used in the strict sense of Platts' methodology documents and refers to a trading participant in the Platts Window who provides a quote before a certain cut-off period. In the traditional sense, the term refers to a liquidity provider, buying and selling an asset on a trading venue.

Market on Close Platts' MOC is a price-discovery system designed to yield a price assessment reflective of market values at the close of the typical trading day. [...] The MOC process is a very structured system for information gathering that allows transparent and fully verifiable market information to form the basis of the daily price assessment (defined by Platts, n.d.a).

Market taker In the context of this dissertation, the term is used in the strict sense of Platts' methodology documents and refers to a trading participant in the Platts Window who hits an existing bid or lifts an existing offer.

Maturity See contract month.

Message An instruction to a trading venue such as a quote submission, quote change, or quote cancellation.

Mid The average of the bid and ask prices.

Multilateral trading facility A multilateral system, operated by an investment firm or a market operator, that brings together multiple third-party buying and selling interests in financial instruments [...] in accordance with [...] Title II of MiFID (Aquilina et al., 2016).

N

Notional The underlying principal value of either an ET or OTC transaction, referred to as the notional value (defined by InfoproDigital, n.d.).

O

Offer See ask price.

Oil major The 'majors' are a group of multinational oil companies given the moniker due to their size, age, or market position. The majors are typically 'integrated' companies, with divisions in exploration, production, marketing, refining, transportation, and distribution (defined by TheStreet, n.d.).

Order An instruction from customers to [...] a trading venue or broker [...], such as a market order, limit order, or conditional order. If the order is 'filled', the trade is executed. If the order is canceled, it is withdrawn (defined by InfoproDigital, n.d.).

Outright order An outright order is a direct price submission in an individual swap contract or a packaged contract.

Over-the-counter Used to describe transactions that are not concluded via a traditional exchange. OTC transactions are often negotiated bilaterally or completed on alternative trading venues.

P

Packaged trade A group of two or more transactions that are executed simultaneously, for a combined price (defined by ClarusFT, n.d.). Common packages such as spreads, butterflies, and curve trades are Required Transactions under the CFTC Trade Execution Requirement.

Paper market A market for contracts where delivery is settled in cash, rather than by delivery of the physical product [...] (defined by InfoproDigital, n.d.).

Physical The underlying physical commodity.

Physical settlement or delivery The settlement of a futures or forward contract by taking/making physical delivery through the transfer of ownership of an underlying commodity between a buyer and seller following expiry (adapted from Platts, n.d.a).

Platts In the context of this dissertation, S&P Global's Platts is the leading oil market PRA.

Platts assessment A Platts assessment is the product of a market survey and the application of strict methodological rules to determine the repeatable tradable price range for a commodity during the assessed period (defined by Platts, n.d.a).

Platts Window The 30-minute assessment period of the Platts Dated Brent benchmark from 16:00 to 16:30.

Post-trade transparency Transaction details are made publicly available, as close to real-time as possible, following their completion.

Pre-trade transparency Information about trading interest (such as quotes) is publicly available.

Price impact [...] the change in the price of an asset caused by the trading of that asset. Buying an asset will drive its price up while selling an asset will push it down (defined by InfoproDigital, n.d.).

Price reporting agency Publishers and information providers who report prices transacted in physical and some derivatives markets, and give an informed assessment of price levels at distinct points in time (defined by IOSCO, 2012).

Q

Quote The price of an asset.

R

Reference price In the context of this dissertation, reference price and benchmark are used as synonyms.

Regulated market A multilateral system operated and/or managed by a market operator, which brings together or facilitates the bringing together of multiple third-party buying and selling interests in financial instruments [...] and which is authorized and functions regularly and in accordance with Title III of MiFID (Aquilina et al., 2016).

Request for quote A marketplace execution method whereby a participant requests prices for a particular instrument [...]. The CFTC requires SEFs to generate three responses to an RFQ (defined by ClarusFT, n.d.).

Required transaction Transactions subject to the trade execution mandate under Section 2(h)(8) of the CEA. These can be thought of as trades meeting MAT criteria [...], and hence need to be transacted on-SEF using RFQ or CLOB (defined by ClarusFT, n.d.).

S

Settlement price A price established at the close of a trading day used to calculate the settlement of futures contracts (defined by Platts, n.d.a).

Short position A position that increases in value if the value of the underlying instrument [...] decreases (defined by InfoproDigital, n.d.).

Speculation The opposite of hedging. The speculator holds no offsetting [...] position and deliberately incurs price risk in order to reap potential rewards (defined by InfoproDigital, n.d.).

Spot market A market where goods are traded for immediate delivery (defined by Platts, n.d.a).

Spot price The price for immediate delivery of a commodity.

Spread The difference between two prices, either across time or between commodities or instruments (defined by Platts, n.d.a).

Standard market size In the context of this dissertation, the standard market size refers to the volume of a standardized trade to be filled theoretically during the assessment of the IRS benchmark. The SMS varies by swap currency and tenor.

Swap execution facility A CFTC designation for an exchange/venue for the trading of OTC derivatives (defined by ClarusFT, n.d.).

Swap spread A general term referring to a packaged transaction/strategy whereby two trades or contracts are combined. For example, a 'swap spread' or 'spread over treasury' refers to the combination of a government bond with an IRS (defined by ClarusFT, n.d.).

T

Trader A market participant who takes part on his behalf in the transfer of a physical or financial asset in OTC or ET markets, for reasons such as investment, speculation, hedging, inventory management, or commercial requirements.

Trad-X Electronic trading venue operated by Tradition.

U

Underlying The variable on which a futures, option, or other derivatives contract is based (defined by InfoproDigital, n.d.).

Upstream Oil and gas exploration and production, as opposed to downstream, which refers to the areas of refining and marketing (defined by InfoproDigital, n.d.).

V

Volume The number of securities or amount of an asset traded.

This is a time of fundamental change in the commodity derivatives markets. The growth of markets, and related financial products, over the longer term, has driven a significant increase in political and regulatory interest.

Lawton, 2014, Director of Markets, FCA

0 Introduction

Decentralized trading networks, also called over-the-counter (OTC) markets[1], have always co-existed alongside organized, centralized exchanges. The OTC markets constitute a crucial component of the global financial system as they offer essential economic functions to institutional participants. OTC trading activity accounts for hundreds of trillions of dollars in notional amount outstanding[2] and takes place in decentralized networks between financial institutions or on a collection of alternative venues such as multilateral trading facilities (MTFs)[3], often only accessible to institutional investors. While these hybrid systems represent a compromise between traditional bilateral OTC markets and centralized electronic order book markets (see Hendershott and Madhavan, 2015), trading is still fragmented across different networks and venues, with implications for

[1] I follow established literature in labeling as OTC, markets that are not legally recognized as centralized exchanges in their jurisdictions (see Bessembinder and Maxwell, 2008).

[2] See the Bank for International Settlements (BIS) OTC derivatives reports at: `https://www.bis.org/statistics/derstats.htm`.

[3] Although very similar to organized exchanges, such as regulated markets (RMs), MTFs differ slightly in that they can be run not only by a regulated market operator but also by an investment firm that brings together third-party trading interests. The key differentiating feature is that operating an MTF is considered an investment service.

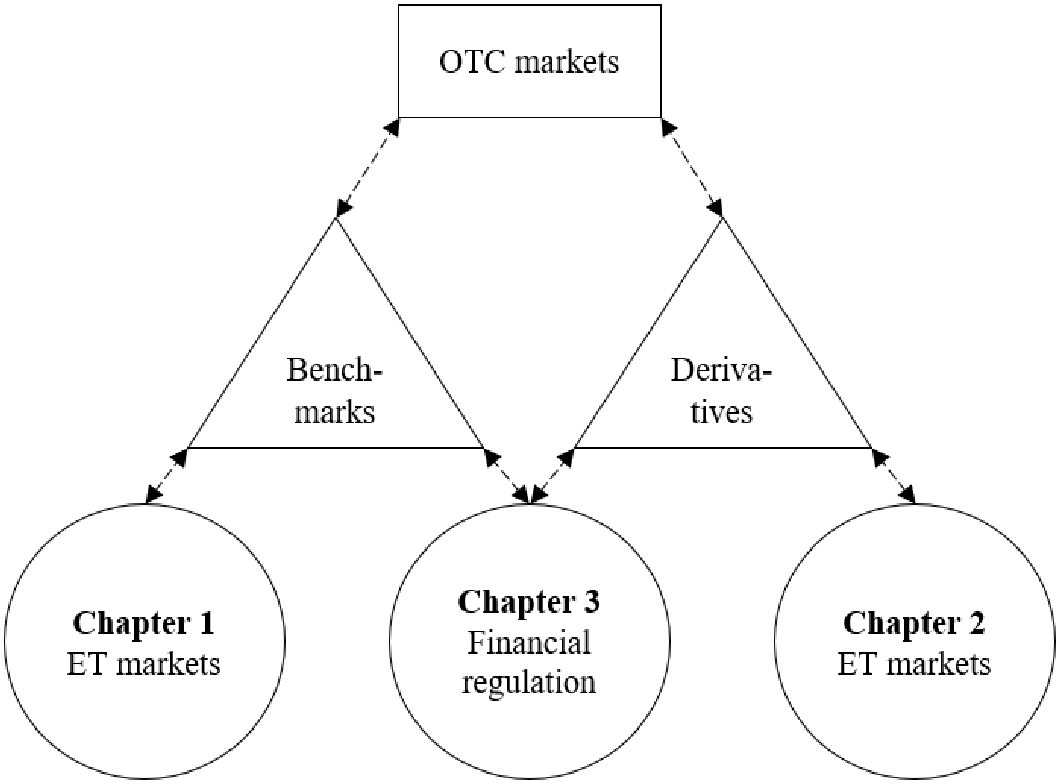
transparency and search costs. Exchange-traded (ET) markets, however, concentrate activity in one primary venue, thereby allowing individual as well as institutional investors direct access to competitive trading in a transparent environment. Over time, innovative financial products and market infrastructure elements have developed to bridge the fragmented structures of OTC and ET markets and ensure the efficient functioning of the overall market. For instance, financial derivatives, as well as reference prices known as benchmarks, ensure orderly price discovery and mitigate frictions between market structures (see Duffie et al., 2017; Jorion, 1995).

Commodity markets are particularly interesting elements of financial markets and our economic system. They consist of well-developed OTC and ET markets that provide economic functionalities to commercial manufacturers, consumers, and speculators, such as risk and inventory management or supply and demand balancing. Liquid organized derivatives markets, often used for risk management purposes, exist alongside decentralized physical commodity markets for fundamental supply and demand trading. A multitude of benchmarks provide investors with price signals and create transparency across market structures by shedding light on the opaque trading of the underlying physical resources. Commodity markets thus connect economies and investors internationally and directly link the physical resources to operational necessities, thereby having immediate implications for both retail consumers and wholesale institutions. For a large part of this thesis, the commodity of choice is oil, because it is the single most important resource underpinning our modern society, used by all of us on a daily basis, be it for driving our cars, traveling between continents, or powering the creation of goods that we consume. As such, the oil market infrastructure is well-developed and the available data are superior and cater to the needs of the studies.

I. Objectives and motivation

If working well, benchmarks, as well as derivatives, should facilitate the discovery of the fundamental values of assets by aggregating information across market structures, should promote market efficiency through increased liquidity and decreased transaction costs, and finally should help hedgers to transfer unwanted price risks to speculators.

Figure 0.1. The concept of the dissertation



Source: author.

This dissertation focuses on the interrelations between decentralized and centralized commodities and fixed income markets. Often physical (spot[4] or cash) contracts are

[4]In commodity markets, the technically correct usage of the term 'spot price' refers to the price for immediate delivery. However, the term 'spot market' is also colloquially employed to refer to the physical market.

traded OTC, while financial (paper) contracts are ET. This thesis comprises three studies, which investigate the topics of price discovery, search costs, and transparency in OTC markets through the lenses of benchmarks and derivatives. The conceptual structure of the thesis is illustrated in Figure 0.1.

Chapter 1 aims to demonstrate the importance of physical commodity benchmarks in modern financial markets. This study is motivated by the fact that many commodity markets remain opaque. For instance, very little is known about the interactions between the physical and financial dimensions of the crude oil market. I hypothesize that benchmarks bridge the informational gap between the transparent and centralized ET financial oil derivatives and the opaque decentralized OTC trading of physical oil. Specifically, this study is intended to enhance our understanding of the implications of the Dated Brent benchmark for Brent futures price discovery.

Chapter 2 investigates how OTC (forward) and ET (futures) oil derivatives create informational links between each other that are affected by trading networks in the physical oil market. Moreover, I analyze how the interaction between the two markets on an intraday level affects the determination of the efficient price of oil. Compiling a novel dataset on OTC forward trading, I use forward trader centrality as a proxy for information on oil supply and demand fundamentals received from upstream or downstream business lines. I hypothesize that valuable information is revealed via forward trading and subsequently incorporated into futures prices.

Lastly, in Chapter 3, I seek to show that well-designed financial regulation can positively impact market quality. Intervention in financial markets by policy makers has long been a contentious topic and a source of heated discussion. First, a theoretical model is presented, predicting that a more precisely assessed benchmark could be welfare improving as it would allow traders to better monitor dealers[5] and therefore reduce

[5]For explanations on the terms ‘trader’ and ‘dealer’, please consult the definitions in the glossary.

noise in the prices and stimulate greater market participation. A more precise benchmark could be achieved by a more transparent benchmark fixing process—analogous to the market-based assessment introduced by the Financial Conduct Authority (FCA) as part of the transition from the ISDAFIX to the ICE Swap Rate. I use this design change that targeted the principal benchmark in the OTC interest rate swaps (IRS) space as a natural experiment to test the hypothesis that the transition had a direct positive impact on the liquidity of the underlying market.

All three chapters have their foundations in the OTC markets literature, to which the topics of benchmarks and derivatives have direct connections. The next section will present the current status of research in more detail.

II. Literature review

A. Over-the-counter markets

OTC markets have long attracted the attention of financial scholars and are central to our understanding of the functioning of financial markets.

Duffie (2012) provides an extensive overview of the state of research on OTC markets and the topics of interest, ranging from asymmetric information, search costs, and transparency to dealer networks.

Relevant for Chapter 1 and Chapter 3 of this dissertation are the topics of search costs and transparency. Duffie et al. (2005) show that search costs, such as pecuniary, opportunity, and time costs, play a significant role in OTC markets. The authors demonstrate that well-connected investors face lower bid-ask spreads and that the prices they receive depend on their search abilities in finding counterparties, the availability of market makers, and their bargaining powers. They conclude that their results are consistent with behavior in certain OTC markets, for example, IRS, where more sophisticated investors obtain better prices. Therefore, smaller investors are typically those with fewer outside options. Indeed, Green et al. (2007), Harris and Piwowar (2006), and Schultz (2001) report wider bid-ask spreads for smaller trades and smaller institutions in the bond market. In general, the inability to locate counterparties can lead to substantial price dislocations (Lamont and Thaler, 2003; Mitchell et al., 2002). Duffie et al. (2007) extend their base setting by incorporating investors' risk aversions, while Vayanos and Wang (2007), Vayanos and Weill (2008), and Weill (2008) broaden the model to multiple-asset cases. A further variation by Weill (2007) studies search frictions in a market where market makers lean against buying or selling pressures. Lagos and Rocheteau (2009) expand the search and bargaining model by removing restrictions on asset holdings, allowing traders to respond to frictions by varying their transaction sizes.

In a similar vein, but slightly different setting, Zhu (2012) models a pre-trade opaque market where so-called quote seekers contact quote providers for prices. Repeated contact signals to the quote provider that the seeker has limited outside options, and he therefore provides a worse price. In addition, the quote providers can learn about their competitors' valuations through the interaction with quote seekers. Lauermann et al. (2018) introduce learning in their search-and-bargaining model with uncertainty and find that buyers and sellers initially fail to trade since they experiment with unrealistic price quotes and subsequently adjust their perceptions of market conditions to reach a transaction price that is approximately market clearing.

Search frictions matter in many other interactions in financial markets, for example in the process of short selling (see Duffie et al., 2002), trading in the interbank lending market (see Ashcraft and Duffie, 2007), liquidity provision during crises (see Lagos et al., 2011), and the determination of the federal funds rate (see Afonso and Lagos, 2015).

Information necessarily plays an essential role in both OTC and ET markets as well. In this context, transparency is often defined as the timeliness of available information about market conditions (see Bessembinder and Maxwell, 2008). Decentralized OTC markets are naturally less transparent than centralized, ET markets, where prices and volumes are more readily observable by all market participants.

Biais (1993) compares centralized and fragmented markets and finds that participants possess different information about their competitors in the former than in the latter, leading their bidding strategies for an asset to deviate. While the price formation process between the two structures is different, the outcome in the form of expected spreads is identical. Following this approach, De Frutos and Manzano (2002) state that centralized pre-trade transparent markets reduce competition for order flow and thus induce less aggressive pricing by dealers as they know more about their competitors' quotes. Fragmented markets, therefore, provide better execution prices. They conclude that increased transparency can have negative impacts on price discovery, liquidity, and welfare. Di Maggio and Pagano (2018) find that market transparency, which is often believed to reduce adverse selection by informed traders and should thus have positive effects on prices, can have the opposite effect because it prevents sophisticated financial speculators from participating in trading. According to them, this has negative externalities as it leads the less sophisticated hedgers to withdraw from the market too, thereby depressing asset prices.

Yin (2005) introduces search costs for liquidity traders into the model of Biais (1993) and draws a different conclusion. Spreads in fragmented markets are wider than in transparent centralized markets. These findings are in line with Pagano and Röell (1996) who find that more transparent trading systems reduce the costs of trading for uninformed traders by decreasing their vulnerability to exploitation by better-informed traders. Spreads in centralized markets are thus generally tighter. Flood et al. (1999) experiment on pre-trade transparent versus pre-trade opaque multiple dealer markets and find similar evidence of wider spreads and lower volumes for opaque markets. However, they show that more aggressive pricing in opaque markets accelerates price discovery. Zhong (2016) shows that the operation of a competitive centralized market alongside an OTC market encourages dealers in the latter to reduce opacity improving the efficiency of fragmented markets. The authors underline that competition-enhancing market structures, such as electronic open limit order books, are beneficial for market quality. However, Bessembinder and Maxwell (2008) emphasize that the optimal level of transparency in OTC dealer markets, such as for bonds, might differ from the optimal level in centralized equity markets.

In the multi-asset market modeled by Asriyan et al. (2017), where information spills over from one asset to the other, the authors are unable to establish a clear answer of whether improved transparency has positive or negative welfare implications. While the theoretical literature on transparency in centralized and fragmented markets is inconsistent, several empirical studies document evidence of increased transparency having a positive effect on market quality. Bessembinder et al. (2006) model and empirically test the effect of the introduction of the Transaction Reporting and Compliance Engine (TRACE), which introduced post-trade transparency in the opaque corporate bond market. Bessembinder et al. (2006) and Edwards et al. (2007) report a significant reduction in execution costs for bonds captured by TRACE reporting. Their findings are in line with Naik et al. (1999), whose model implies better inventory risk sharing for dealers through enhanced market transparency. Goldstein et al. (2007) base their study on the phased introduction of TRACE and find mixed effects on liquidity. Spreads narrow in line with better data and thus negotiating positions of investors, but trading volumes appear to be unaffected. Additionally, the transparency improvements do not impact infrequently traded bonds. Bessembinder et al. (2013) estimate that increased transparency would have similar effects on retail-oriented structured credit products, as it is easier for investors to identify dealer markups and to discern the fair price of securities. Analyzing OTC bonds that benefit from pre-trade transparency through concurrent listings on an electronic 'sister-platform', Chen and Zhong (2017) establish that these bonds benefit from significantly lower transaction costs. The authors attribute this to the improved bargaining positions of the traders vis-à-vis the dealers.

A more recent branch of OTC literature, both theoretical and empirical, focuses on networks in OTC markets. Chapter 2 builds on this literature by using social network analysis (SNA) techniques to infer the impact of OTC trading networks on information incorporation in ET financial markets. For detailed surveys on the application of SNA in economic research, for example in the context of game theory and auctions, please refer to Easley and Kleinberg (2010), Goyal (2005), and Jackson (2005, 2008). The network literature presented below, which focuses specifically on financial markets, and in particular OTC markets, is relatively nascent.

Gale and Kariv (2007) model financial networks, asserting that a network where every possible connection between participants is present resembles a centralized auction market, whereas an incomplete network requires intermediation and corresponds to a decentralized market. Malamud and Rostek (2017) establish that decentralized market structures are welfare improving because they can allocate risk better amongst the participants. Gofman (2014) shows that in an incomplete OTC network large and well-connected financial institutions improve market efficiency by acting as intermediaries. In the OTC framework of Babus and Kondor (2018), the determining feature of dealers' trading costs is the centrality of counterparties to which they are connected, rather than their own centrality in the network. The relationships with well-connected counterparties provide more comprehensive learning opportunities. The authors show that the price impacts and trading costs of central dealers are lower and their traded volumes and profits are higher.

Empirical studies are diverse and focus on a wide range of markets. In the OTC corporate bond market, Hendershott et al. (2017) establish that large insurers with better dealer networks receive more favorable prices than smaller insurers with less elaborate network connections. The authors, however, also find that, due to increased dealer competition in their network, insurers need to trade off good transaction prices and execution speed with price premia charged by dealers for the reduction in repeat business. In line with the search frictions literature discussed above, Li and Schürhoff (2014) find that, in the municipal bond market, highly interconnected central dealers provide more efficient matching of counterparties to their clients, but this comes at the price of higher transaction costs. The central dealers can offer immediacy because they hold larger inventories and have better search abilities. Peripheral dealers, on the other hand, pre-arrange a higher number of trades, taking less risk, and thus compete on execution costs. Di Maggio et al. (2017b) find that dealers value relationships in the inter-dealer corporate bond market and charge significantly lower spreads in the case of longer-standing trading relations. The relationships play an even greater role during periods of market distress. Hollifield et al. (2017) confirm that in the securitized debt market core dealers trade with many different counterparties and receive better prices. Finally, more central credit dealers in the corporate bond and credit default swap (CDS) markets are more skilled in the sense that they are better able to avoid poor trades (Munyan and Watugala, 2017). Ozsoylev et al. (2014) focus on equity markets and confirm that the returns earned by more central investors are higher and that they trade early and in the right direction on information signals, in fact before peripheral investors do. In the asset management space, Di Maggio et al. (2017a) provide evidence of a 'network alpha', as trading information percolates from central brokers to their preferred institutional clients, which then execute profitable trades in the same direction through the broker that provided the information.

The literature is growing fast and extends to investigating the implications of networks for financial contagion (see for example Babus, 2016; Elliott et al., 2014; Leitner, 2005), insider trading (see for example Ahern, 2017), and corporate boards (see for example Cohen et al., 2008; Engelberg et al., 2013).

B. Benchmarks

Benchmarks have long been an integral part of the financial market infrastructure, and OTC markets in particular. Their purpose ranges from signaling prices to monitoring trade executions and settling contracts. Importantly, however, benchmarks can enhance transparency and reduce search costs—two factors that determine price discovery and liquidity in the market. Benchmarks are thus crucial as they alleviate the adverse effects of search frictions and opaqueness in OTC markets discussed in the previous section.

A significant contribution has been made by Duffie et al. (2017), who show that benchmarks are powerful transparency instruments that have the potential to be welfare improving. The authors demonstrate that the introduction of a benchmark in the OTC market improves the information available to traders and reduces their search costs, leading to increased price transparency. For this reason, a benchmark encourages dealers to compete aggressively for the best price, prompts more efficient dealer-trader matching, and increases the volume of beneficial transactions. The raised inter-dealer competition improves market liquidity and reduces transaction costs for traders.

However, given the numerous investigations by regulators into the alleged manipulations of benchmarks, a far more substantial portion of the existing research focuses on trading patterns of financial products around the times of assessment of short-term loans, precious metals, oil, and foreign exchange benchmarks.

For obvious reasons, the London Interbank Offered Rate (LIBOR) attracts particular attention. First, Abrantes-Metz et al. (2012) study the market dynamics around the setting of the benchmark for short-term interest rates, comparing banks' LIBOR quotes to their CDS spreads, and find patterns suggestive of anticompetitive behavior in the 1-month LIBOR rate. Meanwhile, Fouquau and Spieser (2015) apply a novel technique that allows them to detect possible cartels. The identified banks correspond to those classified by the regulator as having played a major role in the 2012 LIBOR scandal. Monticini and Thornton (2013) analyze the conjecture that some panel participants understated their LIBOR submissions and present evidence that this behavior likely led to a reduction in the reported rates. Poskitt and Dassanayake (2015) identify that banks underpriced their LIBOR submissions following pronounced stock price falls, so as to portray favorable creditworthiness, but do not find evidence that the so-called 'lowballing' has biased the benchmark rates downwards. Chua et al. (2017) provide similar evidence of under-reporting as the banks' borrowing costs, proxied by CDS credit spreads, and LIBOR submissions are not in alignment during the period of alleged manipulation. Eisl et al. (2017) analyze the statistical characteristics of the actual LIBOR and Euro Interbank Offered Rate (EURIBOR) benchmark assessments that are based on submissions by panel banks and find that alternative rate-setting procedures (for example based on static approaches using medians instead of trimmed means or dynamic approaches using detection methods for outliers) are less susceptible to manipulation. Coulter et al. (2018) suggest a new assessment procedure for LIBOR that introduces a revelation mechanism that issues fines for submission deviations from an elicited comparison rate. The authors show that the new method curtails manipulation and is an unbiased estimator of the actual benchmark rate. Many more papers deal with the alleged manipulation of reference prices, in particular LIBOR (see for example Abrantes-Metz et al., 2011; Braml, 2016; Gandhi et al., 2018; McConnell, 2013; Muto, 2017; Stenfors, 2014; Stenfors and Lindo, 2018), but I refrain from going into further detail as benchmark rigging is not the focus of this dissertation.

In the precious metal market, Caminschi and Heaney (2014) deduce that information, such as the price direction of the ongoing assessment, is leaking from the physical London pm gold price fixing into the gold derivatives market ahead of the official price publication. Chapter 1 contributes to the literature on price patterns around benchmark assessments in commodity markets, but also to the price discovery role of reference rates at the intersection of OTC and ET markets. I find evidence of enhanced market activity and a consistent price trend of Brent futures in the direction of the benchmark outcome during the Platts Dated Brent assessment. This suggests that physical market activity during the oil benchmark assessment substantially influences the development of the futures price. In equity markets, Griffin and Shams (2018) establish patterns in index options trading that appear to influence the monthly settlement of the VIX index substantially. According to the authors, their findings are consistent with attempted manipulation and inconsistent with alternative explanations.

Finally, a range of papers focus on foreign exchange and the WM/Reuters London 4 pm FX fix. Melvin and Prins (2015) demonstrate that the exchange risk hedging of foreign equity fund portfolios significantly influences the 4 pm fix. Osler and Turnbull (2017) model dealer behavior around benchmark price assessments and derive trading patterns that suggest collusion among participating dealers. El Mouaaouy (2018) detect price anomalies in the FX rates that are more pronounced during periods with collusive chat activity between participating banks and Evans (2018) reports currency price movements around the time of the London fix that contradict the patterns of competitive trading predicted by his model. Although Michelberger and Witte (2016) report dynamics around the time of the FX benchmark fix that distinguish the period from others during the trading day, Ito and Yamada (2017) find little evidence of direct manipulative behavior.

This literature stream on benchmark manipulation and price patterns around assessment times has led to a much more limited set of papers focusing on the design, reform, and regulation of financial benchmarks (see for example Duffie and Dworczak, 2018; Duffie and Stein, 2015; Perkins and Mortby, 2015). Duffie and Stein (2015) propose that (i) benchmarks should be anchored in completed transactions rather than subjective perceptions of market participants and (ii) alternative benchmark reference rates should be used more actively. The authors also acknowledge the vital role to be played by regulators, as market participants are reluctant to opt for competing benchmark rates when they are less liquid, even if manipulation concerns could be alleviated. Duffie and Dworczak (2018) characterize the benchmark design problem faced by benchmark administrators assessing a transaction-based reference rate. They characterize the optimal benchmark as one that puts hardly any weight on small transactions (as it is cheap to manipulate those), equal-weights large transactions, and maybe somewhat surprisingly has a probability of manipulation greater than zero. Chapter 3 of this thesis adds to this growing branch of literature by suggesting a model that theoretically motivates the recent regulatory benchmark interventions. I then provide empirical evidence drawn from the transition to a more transparent and regulated benchmark in the IRS market and the effects it had on the underlying market liquidity.

C. Derivatives

Derivatives 'derive' their value from an underlying asset and can be traded OTC or via centralized exchanges. OTC-traded derivatives, such as forwards, are private bespoke bilateral contracts traded between institutional investors in decentralized networks. ET derivatives, such as futures, are standardized contracts and are traded on centralized exchanges where both individual and institutional investors can participate.

Similarly to benchmarks, derivatives occupy a fundamental role connecting different market structures. They provide a virtually constant link between OTC and ET markets and products that share the same underlying.

Jorion (1995) summarizes the three essential economic functions of derivatives and their importance for the efficient functioning of capital markets: (i) risk management, (ii) transactional efficiency, and (iii) price discovery.

First, derivatives allow risk-averse participants to transfer unwanted risk to more risk-loving counterparties, such as speculators (Jorion, 1995). According to the author, derivatives are valuable and useful hedging tools because they allow risks to be unbundled and managed separately according to the investors' risk profiles. Existing literature focuses on diverse issues such as the corporate usage of derivatives for risk management (see for example Bartram et al., 2009; Froot et al., 1993; Guay and Kothari, 2003; Petersen and Thiagarajan, 2000; Tufano, 1996), hedging of foreign exchange risk (see for example Allayannis and Ofek, 2001; Brown, 2001; He and Ng, 1998), credit risk (see for example Instefjord, 2005; Jarrow et al., 1997; Jarrow and Turnbull, 1995), and long-term forward exposure (see for example Schwartz, 1997).

Second, derivatives increase transactional efficiency (Jorion, 1995). Often, ET derivatives are cheaper to trade because they are standardized, have lower barriers to entry, minimize counterparty risk through clearing houses, and are thus available to a larger and more heterogeneous user base. This means that standardized derivatives are very liquid, allowing traders to enter and exit the market more easily. The underlying cash markets do not usually provide these benefits (Jorion, 1995). Studies suggest that the existence of an options market improves the efficiency of the underlying market (see for example Kumar et al., 1998; Ross, 1976), for instance by mitigating the effects of short sale constraints (see for example Danielsen and Sorescu, 2001; Figlewski and Webb, 1993).

Third, derivatives stimulate price discovery between different markets and instruments. They provide transparent information about equilibrium prices, reflecting the fundamental supply and demand conditions in the market (Jorion, 1995). Moreover, in the context of the OTC literature presented above, Jorion (1995) highlights that centralized and competitive trading in organized exchanges reduces search costs as the derivatives provide hedgers and speculators with visible and fair prices at all times. Consistent with this argument is the report by Craig et al. (1995) that the existence of a futures market complements stock index trading and improves cross-market information revelation around the clock. Moreover, the extensive literature on derivatives-underlying arbitrage (see for example Brennan and Schwartz, 1990; Chung, 1991; MacKinlay and Ramaswamy, 1988; Yadav and Pope, 1990) suggests extensive price discovery activity going on between the different markets to determine the efficient prices of the traded assets. In line with the price discovery role, the introduction of derivatives trading led to faster incorporation of information into the underlying assets (see for example Antoniou and Holmes, 1995; Bae et al., 2004). Stoll and Whaley (1990), Fleming et al. (1996), and Kawaller et al. (1987) show that derivatives prices move ahead of the prices of the underlying assets. Price leadership between derivatives and underlying markets has received substantial attention, with many studies confirming that derivatives impound information first (see for example Booth et al., 1999; Figuerola-Ferretti and Gonzalo, 2010; So and Tse, 2004) or at least occupy an important price discovery role (Chakravarty et al., 2005).

In the oil sphere, much of the literature has focused on the question of a price discovery lead-lag relationship between OTC-traded physical contracts and exchange-traded financial contracts (see for example Bekiros and Diks, 2008; Inci and Seyhun, 2017; Kaufmann and Ullman, 2009; Liu et al., 2015; Quan, 1992; Schwarz and Szakmary, 1994; Silvapulle and Moosa, 1999). Data limitations constrain the studies and thus their results are inconsistent. Some studies report a unidirectional relationship from futures to spot or vice versa, while others describe a bidirectional relationship. I address this in detail in Chapter 2.

D. Relating the literature to my three studies

As elaborated in the previous section, the level of transparency differs between OTC and ET markets (see Pagano and Röell, 1996). Prices, volumes, and transactions in the physical oil market are not easily observable since trading is infrequent and no official organized exchange exists that centralizes the bilateral activity between counterparties. The physical market is dominated by specialized participants with commercial interests in crude oil that differ from the broader range of participants active in the financial oil derivatives market. Hence, in Chapter 1, I analyze the Dated Brent physical oil benchmark and its role in creating transparency and fostering price discovery across market structures by publicly conveying information on the fundamental value of oil from the OTC spot oil market to the ET Brent futures market. While Duffie et al. (2017) model the role of benchmarks in creating transparency in the OTC market itself, in my case, the public announcement of the benchmark price also serves as a signal to other related markets. The derivatives market reacts to the assessment and publication, and thereby connects the two market structures, stimulating overall price discovery by providing a visible price at all times, as stipulated by Jorion (1995).

In Chapter 2, I delve further into the market-connecting role of derivatives (Jorion, 1995) by studying the relationships between the oil forward and futures markets, revisiting the price leadership question on an intraday level (see Kaufmann and Ullman, 2009; Liu et al., 2015). Do ET derivatives incorporate information first (see Figuerola-Ferretti and Gonzalo, 2010)? Moreover, in the OTC forward market, some traders are likely better informed than others, in line with central participants receiving better prices in the debt market or earning higher returns in equity markets (Hollifield et al., 2017; Munyan and Watugala, 2017; Ozsoylev et al., 2014). I extend a similar concept to the OTC commodity market and ask whether or not the trading activities of core forward participants reveal more fundamental information to the ET futures market.

Lastly, as demonstrated by Duffie et al. (2017), benchmarks are important transparency tools in OTC markets, such as that for IRS. In Chapter 3, building on the benchmark reform literature (see Duffie and Stein, 2015), I ask if improving market transparency further through better designed and regulated benchmarks has positive implications for the underlying markets as well, for example, by mitigating the adverse effects of benchmark manipulation caused by outdated assessment procedures (see Coulter et al., 2018; Eisl et al., 2017). Are well-designed policy interventions indeed beneficial for the efficient functioning of financial markets (see Stiglitz, 1993)?

III. Findings and contributions

I contribute to the literature by adding to the understanding of unaddressed concepts and answering long-standing questions.

Chapter 1 underscores the significance of physical commodity benchmarks as integral elements of the global financial market infrastructure. In contrast to the many studies in the academic literature focusing on the manipulation of benchmarks (see for example Abrantes-Metz et al., 2012; Fouquau and Spieser, 2015, and others), I target and empirically analyze their role as drivers of price discovery in commodity markets. I examine ICE Brent Crude futures trading behavior around the time of assessment of the crucial benchmark price in the physical oil market, called Dated Brent. The reference rate is computed daily by the price reporting agency Platts, based on the trading activity in the North Sea oil market. Particular attention is given to the daily 30-minute assessment window leading up to the publication of the Dated Brent price at precisely 16:30 London time—otherwise known as the *Platts Window*. First, I hypothesize that the physical and financial markets for oil are inextricably linked, such that the ICE Brent Crude futures will be alert to the Platts Dated Brent benchmark assessment. Second, based on the informational relevance of the intersection of the OTC and ET oil markets, I ask whether fundamental information from the Platts Dated Brent benchmark assessment drives the Brent futures price in the direction of the imminent Dated Brent reference rate. I provide evidence of a significant increase in futures trading volume and volatility during the ongoing Dated Brent assessment. Informed traders could earn average profits in the range of 8 bps to 24 bps during the 30-minute benchmark assessment by preempting the significant Brent futures price run-up in the direction of the impending benchmark price. In line with the theory of informed trading, a reversal follows the run-up. Besides this, during the Platts Window, I find evidence of trade order imbalances that align with the direction of the ongoing benchmark assessment and an acceleration in the arrival rate of informed traders. These results suggest that the directional trading behavior, likely by speculators or arbitrageurs, is at least partly information-driven. The informational advantage is plausibly gained in the physical crude oil market and revealed during the benchmark assessment process. During this period of heightened Brent futures market activity, the contemporaneous increase in the participation of uninformed traders ensures the transfer of private information from informed traders to the rest of the market. In alignment with the market microstructure literature, the presence of uninformed traders is critical to the price discovery process in the futures market. I conduct a wide range of robustness tests, controlling for correlation between the benchmark assessment and the futures price, and the effects of confounding events. My extensive results suggest that the Dated Brent plays a pivotal role in the discovery of the Brent futures price.

Chapter 2 demonstrates the importance of forward trading networks for the impounding of information into the futures market and identifies the price discovery roles of both oil futures and forwards in the determination of the efficient oil price. The study addresses data limitations from which the previous literature suffered and contributes to the debate on the financialization of commodity markets (see Cheng and Xiong, 2014).

The futures market leads price discovery and incorporates approximately 81% of all innovations into the efficient oil price ahead of the forward market. Given the functioning of the oil market, the futures market is in fact fully responsible for 100% of the price discovery during the vast majority of the trading day. The explanation for this can be found in the structure of physical oil trading, where forward contracts are only actively exchanged during a couple of minutes from 16:25 to 16:30, towards the end of the trading day. This study, however, shows that, once the forward market is trading, albeit for a very short time, it claims a non-negligible 19% of the price discovery share in the oil market. In addition, based on the account-level data at my disposal, I depict the core-periphery structure of the forward Brent, Forties, Oseberg, and Ekofisk (BFOE) market. A selected number of core traders dominate the physical trading of oil, accounting for more than 65% of notional traded. Participants in the periphery interact with each other infrequently but rely more heavily on the core participants, which adopt the unofficial role of physical oil 'market makers'. I utilize the forward trading network to extract a centrality measure that serves as a proxy for fundamental information, likely gained through oil infrastructure stakes and supply chain involvement, the so-called 'skin in the game' of the participants. I demonstrate that a forward transaction by a trader, moving from the least to the most central position in the network, has a significant permanent price impact on the futures market of up to 15 bps over a 10-minute window. This reaction very likely corresponds to the impounding of fundamental information into the futures price that was released to the market through forward trading, a likely scenario given that the dominant traders in the crude oil forward market have close connections to upstream and downstream crude oil business lines.

Finally, Chapter 3 provides a theoretical rationale for many of the recent regulatory interventions by policy makers in the benchmark space. After that, I empirically test the model predictions. The model suggests that regulation that increases the precision of reference rates by introducing more transparency during their assessment can lead to improvements in the market quality of linked financial products. Particularly, traders are better able to monitor dealers. The findings add to recent advancements in the literature highlighting the critical role of benchmarks in financial markets (see Duffie et al., 2017). I use a natural experiment in the $289 trillion IRS market to verify the model. Implemented on 31 March 2015 by the FCA, the key swaps benchmark transitioned from the unregulated panel-based ISDAFIX assessment to the regulated market-based ICE Swap Rate. I study proprietary USD swaps order book data and find a positive impact of the benchmark regime change (BRC) both on the benchmark itself and on the underlying market. Comparing the differential between the proxied execution price of a standard market size (SMS) on-platform trade at the end of the assessment, and the benchmark rate, the representativeness and accuracy of the benchmark rate increased significantly. At the assessment end, the benchmark rate is nearly 70% closer to swap market prices. Also, the main body of the analysis shows that market liquidity improves significantly following the BRC. I use a multitude of metrics, such as quoted spreads, depth, and execution costs. Spreads narrowed significantly, by 14%. Despite quoted depth at the best bid and offer decreasing, the overall 10-level order book depth increased slightly, and executions of SMS orders became cheaper. As an aggregate measure of the effect of the benchmark transition on spreads and depth, the proxied roundtrip costs of completing a buy transaction and a sell transaction decreased by roughly 11% following the BRC. Difference-in-difference panel regressions show that the significant increase in liquidity is more pronounced for benchmark-grade swaps, i.e., swaps for which a regulated benchmark rate is assessed daily, than for non-benchmark-grade swaps following the transition to the ICE Swap Rate. The findings demonstrate that the introduction of the BRC had a positive effect on the liquidity of benchmark-grade swaps over and above other influences, such as increases in venue participation.

The main distinguishing feature between benchmark- and non-benchmark-grade swaps is the assessment of a regulated and supervised benchmark rate. I therefore directly link the improvement in on-platform execution costs to the regulatory intervention by the FCA. The results are robust to controlling for multiple confounding events and to using alternative regression specifications. Finally, endogenous tests for structural breaks in the time series of the employed liquidity measures confirm earlier results and suggest significant changes in the long-term mean took place imminently before the BRC.

The remainder of this dissertation is organized as follows: Chapter 1 discusses the results regarding the importance of the Dated Brent benchmark for Brent futures. Chapter 2 reports the findings on trading networks in the forward oil market and their impact on the futures market. Chapter 3 presents the analysis of the methodological changes to the leading IRS benchmark and its regulation by the FCA, and the impact this policy intervention had on the underlying market. Finally, in Chapter 4, I discuss the implications of the findings and conclude. The interested reader can find more information, as well as complementary analysis conducted as part of these papers, and the respective results, in Appendix A.

1

The impact of commodity benchmarks on derivatives markets: The case of the Dated Brent assessment and Brent futures

Abstract

I examine the response of ICE Brent Crude futures to the spot Dated Brent benchmark published by Platts. Trading activity in the futures market intensifies during the benchmark assessment. I also find trading in the direction of the published benchmark during the price assessment window. Aligned positions and a substantially increased arrival rate of informed traders suggest that sophisticated traders, taking advantage of a rise in uninformed trading activity, induce the price run-up in Brent futures, ahead of the Dated Brent assessment ending point. The general increase in the arrival rates of both informed and uninformed traders during the assessment window underlines the benchmark's relevance and its potential for attracting liquidity. The results are robust to alternative specifications and underscore the significance of physical commodity benchmarks as critical elements of the financial market infrastructure.

JEL classification: G13, G14, Q02, Q41.

Keywords: Dated Brent, physical crude oil, benchmark assessment, Brent futures

I. Introduction

Benchmarks occupy a central role in stimulating the flow of information between exchange-traded and over-the-counter (OTC) instruments by establishing settlement prices and improving transparency (see Duffie et al., 2017). Due to their importance, benchmarks and their administration are increasingly gaining the attention of regulatory bodies in relation to their architecture and the regulatory oversight they are or should be subjected to (see FCA, 2017).[1] With regards to oil, the most actively traded and one of the most economically important commodities in the world, the International Organization of Securities Commissions (IOSCO) has set out recommendations aimed at enhancing the quality and reliability of its price benchmarks. Nevertheless, the administration of spot oil benchmarks currently remains unregulated. The EU legislation on benchmarks, to be applied from January 2018 onwards, will be the first comprehensive regulatory framework under which physical commodity benchmarks can be considered for direct supervision. Several price reporting agencies (PRAs)[2] currently assess and publish oil benchmark prices. However, the Dated Brent benchmark, operated by S&P Global's Platts, has come to dominate this space. The Platts Dated Brent benchmark prices approximately 67% of the global physical (spot) oil traded (Davis, 2012). This dominance also underscores its importance to the derivatives/financial (paper) markets

[1]In 2012, the International Organization of Securities Commissions (IOSCO) published the *Principles for Oil Price Reporting Agencies.* Starting with the LIBOR, the Financial Conduct Authority (FCA) introduced the first regulatory benchmark regime in April 2013. Two years later, in April 2015, the FCA expanded its regulatory supervision to seven other key benchmarks: LIBOR, SONIA, RONIA, WM/Reuters London 4 pm Closing Spot Rate, ISDAFIX, LBMA Gold Price Fixing, LBMA Silver Price Fixing and the ICE Brent Index (FCA, 2017). The 2015 and 2016 *Fair and Effective Markets Reviews*, conducted by the Bank of England (BoE), HM Treasury (HMT), and the FCA, identify several shortcomings in the Fixed Income, Currencies, and Commodities (FICC) markets and, from July 2016, the *Market Abuse Regulation* (MAR) has regarded the manipulation of benchmarks as a civil offence across the EU. The *EU Benchmarks Regulation* will enter into force at the beginning of 2018.

[2]PRAs classify themselves as media organizations and information providers, collecting and channeling commodity market intelligence into independent benchmark prices. The four major PRAs are Platts, Argus, ICIS and OPIS.

for oil.

Following unannounced searches of the offices of several crude oil market participants by the European Commission and the European Free Trade Association (EFTA)[3] in early 2013, reports of price distortion of the Platts Dated Brent benchmark began to emerge in the financial press (see as examples Kemp, 2013; Mackey and Lawler, 2013; Makan, 2013; Van Voris et al., 2013). More recent news suggests that trading activities at the interface between the physical and financial oil market are still controversial (see as examples Cooper, 2017; Hurst and Blas, 2017). Despite these reports, a limited number of studies have analyzed the impact of the Dated Brent benchmark assessment on financial oil markets more generally. To the best of my knowledge, only Inci and Seyhun (2017) and Swinand and O'Mahoney (2014) have utilized Platts benchmark data. Inci and Seyhun (2017) examine the market dynamics between the spot and futures markets and report a high level of integration, while Swinand and O'Mahoney (2014) examine calendar spreads in order to identify instances of price anomalies in the Brent crude complex. The difficulty in using calendar spreads lies in the increasing level of spread mispricing as the front-month futures contract approaches maturity (see Frino and McKenzie, 2002).

In this paper, I examine trading behavior in the ICE Brent Crude futures contract around the assessment of the Dated Brent benchmark price, computed daily by Platts based on the trading activity in the North Sea spot oil market. Of particular interest is the 30-minute window from the start of the daily Dated Brent price assessment to its end at precisely 16:30 London time—otherwise known as the *Platts Window*. Specifically, based on the assumption of a pricing error-correction relationship (e.g., Hasbrouck, 1995) between the physical and financial oil markets, I hypothesize that both markets

[3]Please refer to http://www.shellnews.net/documents/WhiteOaksFund.pdf and https://web.archive.org/web/20151025003015/http://www.businessweek.com/pdfs/crude-complaint-11-6.pdf for further information.

are integrally linked such that Brent futures will be sensitive to the Platts Dated Brent benchmark assessment. Secondly, based on the informational relevance of the intersection of the two crude oil market dimensions (i.e., the physical and financial oil markets), I investigate whether participants in the Platts Dated Brent benchmark assessment, having become privy to the trading pressure evidenced during the assessment, drive the Brent futures price in the direction of the Dated Brent benchmark.

The results provide evidence of a significant increase in trading activity in the ICE Brent Crude futures contract during the Dated Brent price assessment. I also show that an informed trader could earn average profits of between eight bps and 24 bps during the 30-minute benchmark assessment period, as Brent futures experience a significant price run-up in the direction of the impending benchmark price. The price run-up is followed by a price reversal. Furthermore, benchmark-aligned trade order imbalances and acceleration in the arrival rate of informed traders during the Platts Window suggest that the directional trading behavior is at least partly information-driven.[4] Nevertheless, uninformed traders also participate in the Brent futures market during the Platts Window. Indeed the presence of uninformed traders is critical to the price discovery process in the futures market. Glosten and Milgrom (1985) and Kyle (1985) show that informed traders earn arbitrage gains when trading with uninformed traders. This form of price discovery ensures the transfer of private information from informed traders to the rest of the market.

This study makes two key contributions to the literature. Firstly, I undertake an empirical analysis of the fundamental spot crude oil event, the Dated Brent benchmark assessment, and the intraday response of Brent futures traded on ICE Futures Europe.

[4] Data limitations complicate my attempts to disentangle the trading practices leading to directional trading behavior. However, the common feature making the directional trading worthwhile is, arguably, an informational advantage, most plausibly gained in the physical crude oil market. In this paper, given the findings, I reason in favor of informed trading activity leading to a 'correct' futures price adjustment during the ongoing physical benchmark assessment.

The results underscore the significance of physical commodity benchmarks as integral elements of the global financial market infrastructure and price discovery in commodity markets. Secondly, the analysis of information-related interactions between two market structures is unique in that the Platts benchmark assessment window provides a natural experiment in which to examine the dynamics between the oil spot and derivatives markets. This differs from other fixing events such as in the precious metals market, where the length of the benchmark fixing period is indeterminate (see Caminschi and Heaney, 2014), or those information events that do not have a precise release timestamp (see Bernile et al., 2016; Tetlock, 2010; Vega, 2006).

The remainder of this article is organized as follows: the next section (II) presents the institutional background to the study and discusses the existing related literature; Section III introduces the data; Section IV sets out the methodology and results; and Section V concludes.

II. Background

A. Institutional details

Variability in the grades of oil available for trade at any point in time compels spot traders to apply 'formula pricing' to value any contracted cargo of crude oil, by adding or subtracting a spread to an agreed benchmark price, as calculated by a PRA (Dunn and Holloway, 2012). The PRA publishing the industry-leading benchmark price for Dated Brent is Platts.[5] Dated Brent refers to the price of a physical cargo of North Sea Brent, Forties, Oseberg or Ekofisk (BFOE) crude oil with an assigned loading date for shipping—a *dated* cargo. Platts operates an online data-entry and communications

[5]Dated Brent is estimated to serve as a price marker for anywhere between 50% and 80% of the world's physical crude oil trade (see Barret, 2012a,b; Davis, 2012; Dunn and Holloway, 2012; Mathur, 2013; Tuson, 2014).

system called *eWindow* that is used to establish the Dated Brent benchmark price in the Market on Close (MOC) process.[6] The MOC methodology has the advantage of promoting liquidity, as it concentrates spot market activity over a short timeframe at the end of the day (Barret, 2012a). The investigation focuses on the daily half-hour (16:00–16:30) window during which the Dated Brent is computed. During this half-hour assessment window, Platts considers a combination of three physical OTC variables: (i) physical North Sea cargoes, (ii) short-term swaps between Dated Brent and forward Brent (i.e., Contracts for Differences, CFDs), and (iii) outright forward Brent (also called cash BFOE). The window itself can be divided into three phases, determined by cut-off periods. During the first phase, market participants submit new bids/offers for physical North Sea cargoes, traded as a differential from the Dated Brent or forward Brent; the new entry cut-off for this is 16:10:00. New bids/offers for CFD contracts are assessed in the second phase, with a new entry cut-off of 16:15:00. The third cut-off for new outright cash BFOE bids/offers is 16:25:00. Notwithstanding the specified cut-offs for new entries, existing physical North Sea bids/offers and CFD bids/offers may be amended until 16:25:00. Finally, prices for cash BFOE can be changed until the window closes at 16:30:00. This last phase is judged to be of critical importance and described as particularly stressful for both Platts and the physical market participants, not least because cash BFOE is the last and only element of the assessment traded at a flat price. Based on these three inputs, Platts calculates a price for each of the four North Sea grades (Brent, Forties, Oseberg, and Ekofisk),[7] with the cheapest grade setting the daily Dated Brent price. The Dated Brent price reflects the tradable value at precisely 16:30:00 London time.

Only a limited number of companies, mastering the operational and logistical requirements of trading spot oil, participate in physical oil trading via eWindow. The firms

[6] Please refer to Appendix I for more details.
[7] Prices for the four grades vary due to differing oil qualities.

are also required to satisfy Platts' due diligence requirements. According to multiple sources and discussions with the industry, there is only a handful of active trading companies participating each day (see also Barret, 2012a; Fattouh, 2011). In addition to the trading participants, a larger but still limited number of subscribers to Platts' fee-based Global Alert (PGA) real-time information service can follow the live physical trading activity and order-flow information (transactions, bids, asks) throughout the benchmark assessment period.[8]

B. Related literature

Recent theoretical research by Duffie et al. (2017) highlights the key role benchmarks play in enhancing price transparency and liquidity in the underlying market. Several empirical studies examine the effects of benchmarks and their operation on the trading behavior in related derivatives, some reporting a positive and others a negative impact. This literature is limited and restricted to the precious metals, fixed income, and foreign exchange markets. The assessment procedures of these markets differ significantly from that of the oil market.

In the precious metals market, Caminschi and Heaney (2014) examine the short-term reaction of gold futures and exchange-traded funds (ETF) to the London pm gold price fixing, and conclude that information from the benchmark assessment proceedings (for example, price direction) leaks into the gold derivatives market well before the official price publication. Similarly, Aspris et al. (2015) investigate the effects of the replacement of a traditional closed fixing auction for precious metals with a more transparent and enhanced electronic-based auction platform on related futures contracts. They show

[8] I interchangeably refer to the Platts process as assessment or fixing. Unlike those for several other commodities, such as in the precious metals market, the physical oil market has no official fixing system. However, over time, a few PRAs have adopted the role of benchmark administrators.

that the new regulated regime leads to a significant improvement in market quality. In terms of the fixed income market, several studies examine market dynamics in relation to the London Interbank Offered Rate (LIBOR). Abrantes-Metz et al. (2012) describe patterns suggestive of collusion and manipulation of the 1-month LIBOR rate, while Fouquau and Spieser (2015) find that their identification of manipulating banks corresponds to those classified by the regulator as having played a major role in the 2012 LIBOR scandal. Monticini and Thornton (2013) show that the under-reporting of LIBOR quotes by certain participating banks likely led to reduced rates. Additionally, Evans (2018) reports asymmetric behavior in price changes and volatility for 21 currency pairs during the WM/Reuters London 4 pm FX benchmark fixing period vis-à-vis normal trading periods. Contrary to the expectations of dealers sharing risks, Evans (2018) identifies trading strategies consistent with collusive and manipulative behavior that lend themselves to significant economic trading opportunities. More recently, several studies have focused on the reformation of financial benchmarks in light of a number of regulatory investigations (e.g., Duffie and Stein, 2015; Perkins and Mortby, 2015).

The benchmark structure, process, and operation in these markets are, however, different to those in place for oil markets in terms of design, transparency, and regulation. The question remains: what is the observed response of the paper oil market to the assessment of the key spot oil benchmark?

C. *Directional trading*

Directional trading—the adoption of a futures position during the assessment window that is aligned with the benchmark outcome,[9] can result from a number of different trading practices by different participant groups. For example, such trading behavior could be due to an intention to manipulate the market by influencing the direction of

[9]In the context of this paper, directional trading strictly refers to this definition, and not to other strategies such as directional options trading.

the benchmark price and simultaneously executing an aligned futures position. Makan (2013) cites an anonymous trader who, in an interview with the Financial Times, states that "[t]he game of having a leveraged position in the futures market and then trying to change the Platts price by a few cents is as old as the market itself". While alleged manipulation may be one possibility, it is not within the scope of this study. Secondly, a trader could also anticipate the benchmark direction through Brent futures speculation based on intelligence gained in the physical spot market, through either commercial participation or proprietary commodities trading, for example. A third reason is linked to spot-futures arbitrage activity based on the fundamental value relationship between spot and futures. Arbitrageurs are strictly defined as being informed from a market microstructure perspective (e.g., Chordia et al., 2008; Moore and Payne, 2011), and thus contribute to the futures price discovery during the Platts assessment window by speedily translating information from the spot market into futures prices. Fourthly, trading in futures could further arise due to natural hedging activity carried out by commercial users in order to cover physical exposure. The common feature making any of the above worthwhile is arguably an informational advantage, most plausibly gained in the physical crude oil market. As an example, consider a physical market participant such as a commercial user who is closely monitoring the oil market and is thus informed of spot market fundamentals such as demand and supply. The informed trader can try to anticipate the dynamics during the Platts Window and align his futures positions accordingly. Benchmark submitters naturally belong to this category of traders. Alternatively, as physical trade and order flow is revealed during the Platts assessment, an informed trader can continuously judge the extent to which the information is being incorporated into the futures price, and act if he identifies a divergence from the fundamental spot-futures relationship. Both examples would lead to a futures price adjustment in the direction of the Dated Brent fixing outcome, ahead of the end of the assessment period.

Wang (2002) and Frino et al. (2016) argue that hedgers may indeed be informed, given their proximity to the underlying good or customer, and this may also hold true for the spot oil market. In this case, however, the hedging theory does not align with the results presented in this paper. In order to hedge a physical transaction executed during the Platts Dated Brent benchmark assessment, a futures position in the opposing direction to the spot fixing would need to be adopted. As illustrated above, the more plausible explanations are physical-market-informed futures speculation or spot-futures arbitrage.

III. Data and study design

Intraday data for the ICE Brent Crude futures and the Brent-Forties-Oseberg (BFO) crude oil spot, with identifiers LCOc1 and BFO− respectively, are obtained from the Thomson Reuters Tick History (TRTH) database.[10] Both datasets include trade and quote information, timestamped to the nearest millisecond. The Brent Crude futures are listed for each month, seven years forward, and are cash settled against the ICE Brent Index.[11] I sample only the front-month, closest-to-maturity futures contract and roll over to the next contract at expiry.[12] The BFO spot price, constructed by Thomson Reuters, is based on a combination of the futures price (either ICE Brent or NYMEX WTI, depending on the time of day), Exchange of Futures for Physical (EFP)[13] values, and the ICE close. The BFO serves as a public estimate of the intraday oil price in light of the OTC nature of oil markets. I use the BFO series as an approximation of

[10]There is no BFOE crude oil spot price proxy available via TRTH. Hence, I use the dated BFO price, which is the closest proxy.

[11]The analysis does not focus on the ICE Brent Index that is only published on a monthly basis for cash settlement purposes, following the expiry of the ICE Brent Crude futures front-month contract.

[12]Using only the nearest-maturity contracts is consistent with the literature on commodity derivatives. This is mainly because the nearby futures contract is typically the most liquid, whereas the longer-dated contracts are predominantly thinly traded.

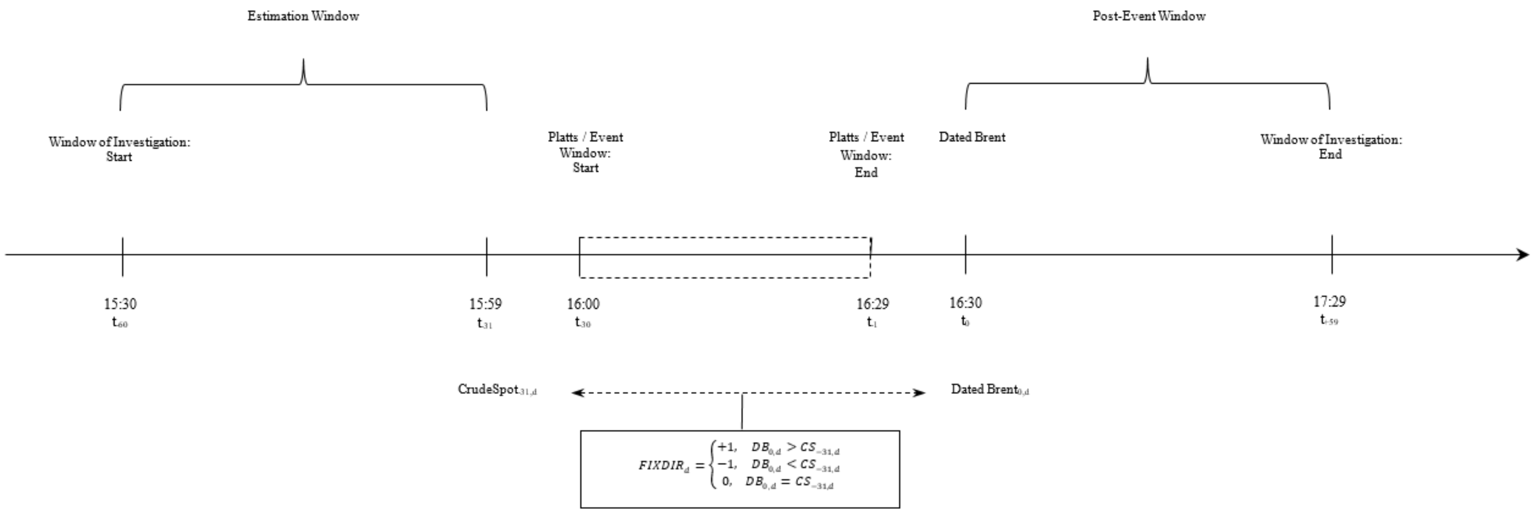
[13]An EFP allows traders to exchange a Brent futures position for a cash BFOE (forward) position and vice versa.

the Brent crude oil spot price immediately ahead of the Platts Window starting time at t_{-31} = 15:59 (see Figure 1.1). Finally, I acquire price data for the daily Dated Brent benchmark, with identifier PCAAS00, from Platts Singapore. The Platts data contain daily Dated Brent prices timestamped at 16:30 London time. The full period of investigation comprises observations from 9 January 2012 to 31 March 2016 inclusive, some 1,056 trading days.

I sample data over a 120-minute window of investigation [t_{-60} = 15:30, t_{+59} = 17:29], covering the hour before and hour after the end point of the Dated Brent assessment for each trading day d, as depicted in Figure 1.1. The pre-benchmark *estimation window* is [t_{-60} = 15:30, t_{-31} = 15:59] and the *post-event window* [t_0 = 16:30, t_{+59} = 17:29]. The *event time*, t_0 = 16:30 London local time, refers to the start of the minute-long interval covering the 16:30:00 Platts Dated Brent price. The Platts assessment or *event window* encompasses [t_{-30} = 16:00, t_{-1} = 16:29].[14]

[14]All time specifications are in London local time. During the summer time, London local time corresponds to British Summer Time (BST = GMT + 1), whereas during the winter, London local time corresponds to GMT. BST begins at 01:00 GMT on the last Sunday of March and ends at 01:00 GMT on the last Sunday of October.

Figure 1.1. Window of investigation



Notes: This figure illustrates the event study design applied to analyze trading behavior surrounding the Platts Dated Brent price assessment. *DB* and *CS* represent the price of Dated Brent and the BFO crude spot in interval t on trading day d, respectively. Timestamps represent interval start times. The estimation window covers interval t_{-60} to t_{-31} [15:30:00, 15:59:59]. The event window covers t_{-30} to t_{-1} [16:00:00, 16:29:59]. The post-event window covers t_0 to t_{+59} [16:30:00, 17:29:59].

IV. Empirical analysis, results, and discussion

A. *Relative volume and volatility evolution around the Dated Brent benchmark assessment*

In a similar way to Caminschi and Heaney (2014), I begin my analysis by examining the evolution of ICE Brent Crude futures intraday relative volume and volatility around the Dated Brent benchmark assessment window. I compute these measures for each interval t during the window of investigation, relative to a reference value measured over the 30-minute estimation window, $[t_{-60} = 15{:}30,\ t_{-31} = 15{:}59]$, for each trading day d, and then average across all sample trading days D. The 30-minute estimation window reflects the average level of activity on d, independent of the benchmark assessment process.

The average relative volume per interval t is computed as follows:

$$VMref_d = \frac{1}{30} \sum_{t=-60}^{-31} \ln\left(VM_{t,d}\right) \tag{1.1}$$

$$\overline{VM_t} = \frac{1}{D} \sum_{d \in D} \frac{\left(\ln\left(VM_{t,d}\right) - VMref_d\right)}{VMref_d} \tag{1.2}$$

where $VM_{t,d}$ is defined as the total trading volume in Brent futures during any given one-minute interval t on day d. $\overline{VM_t}$ is the average difference, for each one-minute interval t, between the log volume and the reference volume on day d, scaled by the reference volume on d such that it yields the percentage volume increase or decrease relative to the estimation window. The log transformation normalizes the data, mitigates the skewness effect caused by the zero bound on volume, and improves the robustness of the subsequent t-tests (Caminschi and Heaney, 2014).

To measure Brent futures price volatility for each interval t of the window of investigation, I compute the standard deviation of one-second returns within each one-minute interval t on trading day d, and follow the same rationale as described in Equation 1.1 and Equation 1.2.[15]

Results for the relative trading volume and volatility are reported in Figure 1.2 and Table 1.1. For parsimony, I only report the sub-window [t_{-35} = 15:55, t_{+5} = 16:35] of the full 120-minute window under investigation in Table 1.1. This sub-window covers five minutes before the start and five minutes after the end of the assessment period; the approach does not result in any loss of information.

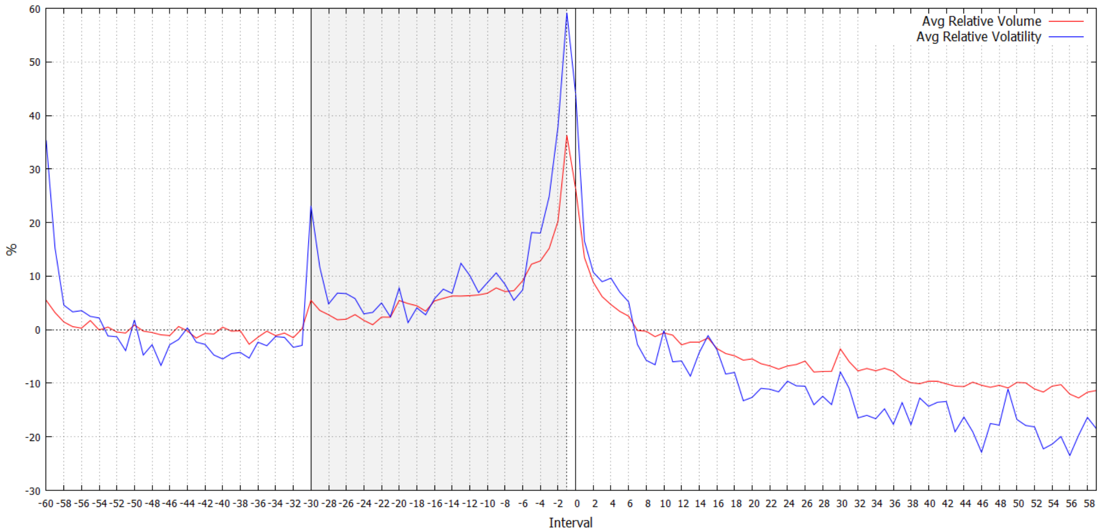
Relative volume, as well as relative volatility, show increased values during the Platts Dated Brent price assessment. For $\overline{VM_t}$ in Panel A of Table 1.1 and Figure 1.2, the increase in trading intensity coincides with the start of the Platts Window (t_{-30} = 16:00) and falls sharply thereafter (t_{+1} = 16:31). Average relative trade volume for ICE Brent Crude futures inflates by approximately 5.5% at the fixing start and rises to 36.3% above pre-benchmark-assessment levels, with the highest trading volume recorded immediately prior to the end of the assessment (t_{-1} = 16:29). Following the completion of the fixing, $\overline{VM_t}$ gradually reverts to pre-event levels. The increase in relative trading volume is statistically significant at the 1% level and persists for 30 minutes. Panel B of Table 1.1 and Figure 1.2 report the volatility behavior in ICE Brent Crude futures contracts. Relative volatility increases significantly by 23.1% immediately after the fixing start, and remains several percentage points above estimation window levels for the next

[15] I also compute the Garman and Klass (1980) volatility estimator, specified as follows:

$$V_{t,d} = \sqrt{\frac{1}{2}\left(\ln\left(\frac{H_{t,d}}{L_{t,d}}\right)\right)^2 - \left(2\ln(2) - 1\right)\left(\ln\left(\frac{C_{t,d}}{O_{t,d}}\right)\right)^2}$$

where $H_{t,d}$, $L_{t,d}$, $O_{t,d}$, and $C_{t,d}$ refer to the high, low, open, and close prices for interval t on day d respectively. The results obtained with this approach are qualitatively similar to those reported for the one-minute standard deviation estimates. Moreover, I calculate the average relative trade size using the same approach. For parsimony, the results, which are consistent with other trading activity measures, and a short discussion are presented in Appendix II to this paper.

Figure 1.2. Average trading activity in ICE Brent Crude futures



Notes: This figure shows the average relative volume and volatility. All measures are reported in percentage terms (%). The shaded area indicates the event window from fixing start (t_{-30}) to fixing end (t_{-1}) [16:00:00, 16:29:59]. The vertical black line marks the interval following the Platts Dated Brent assessment end: t_0 [16:30:00, 16:30:59].

15 minutes (from t_{-28} = 16:02 to t_{-14} = 16:16). Volatility rises significantly again and peaks at 59.2% above estimation levels just before the end of the Dated Brent window at 16:30. The last five minutes of the benchmark assessment period are characterized by a particularly volatile futures market. As I observe in relation to volume, volatility declines at the end of the fixing period and remains depressed during the post-event window (see Figure 1.2). Overall, the results for the intervals during the 30-minute Platts Window, from 16:00 (t_{-30}) to 16:29 (t_{-1}), are for the most part significantly different from zero for both measures. Trading activity peaks immediately before the Platts Window ends and is succeeded by a general decline thereafter.

Collectively, these findings strongly support the expectation that the financial oil market is sensitive to the Platts Dated Brent benchmark assessment, highlighting that the benchmark process is an essential spot crude oil information event. The trading activity results imply that an unusually high number of traders arrive at the market after the start of the fixing and prior to its end, as demonstrated by the high volume, and that the Brent futures market is uncommonly 'alert and nervous' during the event window, as documented by the volatility levels. In the following sections, I further examine this view by analyzing the evolution of informed trading around the benchmark period.

B. *Returns analysis around the Dated Brent benchmark assessment*

In order to evaluate my expectations regarding informed directional trading, I compute the *simple* and *directional returns* available to both 'uninformed' and 'informed' participants, respectively. The directional returns are a measure of hypothetical gains available to a trader who has an informational advantage over the general market. It is plausible that the informational advantage is derived from physical oil market intelligence, enabling, for example, futures speculation based on an ex-ante approximation of the direction of the Dated Brent benchmark assessment, or spot-futures arbitrage incorporating information as the fixing progresses.

B.1. Simple returns

Simple returns are those available to a random long-only investor, measured using the closing price $C_{t,d}$, for each one-minute interval t on trading day d. I standardize the returns across the sample periods as follows:

$$SR_{t,d} = \ln\left(\frac{C_{t,d}}{C_{t-1,d}}\right) \tag{1.3}$$

$$\overline{SR_t} = \frac{1}{D}\sum_{d \in D} SR_{t,d} \tag{1.4}$$

$$CSR_t = \sum_{t=-60}^{t} \overline{SR_t} - \sum_{t=-60}^{-31} \overline{SR_t} \tag{1.5}$$

Table 1.1. Trading activity in ICE Brent Crude futures

		Panel A			Panel B		
		Avg Relative Volume			Avg Relative Volatility		
t_i	*Time*	*VM*	*Sign*	$t-value$	*V*	*Sign*	$t-value$
-35	15:55	-0.28		-0.52	-3.00	*	-1.68
-34	15:56	-1.11	**	-2.17	-1.28		-0.52
-33	15:57	-0.62		-1.15	-1.43		-0.7
-32	15:58	-1.49	***	-2.83	-3.29		-1.49
-31	15:59	0.19		0.32	-2.93		-1.44
-30	16:00	5.49	***	8.55	23.13	***	6.21
-29	16:01	3.60	***	5.64	11.70	***	3.93
-28	16:02	2.78	***	4.79	4.81	*	1.81
-27	16:03	1.85	***	2.9	6.83	**	2.18
-26	16:04	1.95	***	3.04	6.73	**	2.52
-25	16:05	2.82	***	4.43	5.81	**	2.22
-24	16:06	1.74	***	2.75	2.96		1.07
-23	16:07	0.92		1.44	3.23		1.1
-22	16:08	2.35	***	3.99	5.00	*	1.65
-21	16:09	2.33	***	3.5	2.39		0.82
-20	16:10	5.45	***	7.99	7.78	***	2.62
-19	16:11	4.88	***	7.71	1.31		0.54
-18	16:12	4.47	***	7.25	4.07		1.37
-17	16:13	3.46	***	5.36	2.77		1.02
-16	16:14	5.36	***	8.05	5.78	**	2.04
-15	16:15	5.85	***	9	7.57	**	2.49
-14	16:16	6.29	***	10.49	6.79	**	2.08
-13	16:17	6.28	***	10.16	12.40	***	3.44
-12	16:18	6.35	***	10.17	10.12	***	2.95
-11	16:19	6.49	***	10.04	6.94	**	2.14
-10	16:20	6.81	***	10.7	8.79	***	2.86
-9	16:21	7.80	***	12.75	10.61	***	3.36
-8	16:22	7.12	***	10.69	8.46	***	2.83
-7	16:23	7.28	***	11.52	5.49	**	2.14
-6	16:24	9.15	***	15.94	7.43	***	3.77
-5	16:25	12.24	***	20.51	18.14	***	4.33
-4	16:26	12.84	***	20.37	18.04	***	6.76
-3	16:27	15.17	***	28.14	24.86	***	8.45
-2	16:28	20.27	***	36.95	37.91	***	11.57
-1	16:29	36.29	***	63.55	59.18	***	18.98
0	16:30	26.33	***	46.44	44.08	***	16.46
1	16:31	13.46	***	22.82	16.55	***	5.93
2	16:32	8.85	***	14.11	10.72	***	3.61
3	16:33	6.18	***	10.34	8.96	***	3.06
4	16:34	4.69	***	8.46	9.62	**	2.47
5	16:35	3.42	***	5.77	7.02	*	1.84

Notes: This table reports the results of the average relative trading activity measures. Panels A and B present the results for the average relative volume and the average relative volatility respectively. Both measures are reported in percentage terms (%). The t-value is the statistic of a one sample t-test of the mean being equal to zero. *, **, and *** correspond to statistical significance at 10%, 5%, and 1% levels respectively. Sample period is 09.01.2012–31.03.2016. Timestamps represent interval start times. The two single horizontal black lines represent the Platts Dated Brent fixing start and fixing end. The interval following the Platts Dated Brent assessment end is t_0 [16:30:00, 16:30:59] London local time.

$\overline{SR_t}$ describes the returns for interval t averaged across all trading days D; CSR_t measures cumulative simple returns in excess of an offsetting factor (see Equation 1.5) such that $CSR_{-31} = 0$ (Caminschi and Heaney, 2014), making it easier to determine the evolution of cumulative returns during the benchmark assessment process [$t_{-30} =$ 16:00, $t_{-1} =$ 16:29].

B.2. *Directional returns*

In order to measure returns attributable to an informed trader who trades in the direction of the benchmark assessment outcome in advance of its release, I compute directional returns. I follow Ederington and Lee (1995) and Caminschi and Heaney (2014) and sign simple returns using a spot fixing direction parameter. The direction factor takes the value of +1 (−1) if the published Platts Dated Brent price (t_0) on day d is higher (lower) than the price of the BFO crude oil spot on d immediately prior to the start of the Platts Window (t_{-31}), assuming that the informed trader takes a long (short) position (see Figure 1.1). Based on this, the sample contains 527 positive, 521 negative, and 8 flat assessment days. Directional returns are hypothetical, and measured for each one-minute interval t as follows:

$$FIXDIR_{t,d} = \begin{cases} +1, & DB_{0,d} > CS_{-31,d} \\ -1, & DB_{0,d} < CS_{-31,d} \\ 0, & DB_{0,d} = CS_{-31,d} \end{cases} \tag{1.6}$$

$$DR_{t,d} = FIXDIR_{t,d} \times SR_{t,d} \tag{1.7}$$

$$\overline{DR_t} = \frac{1}{D} \sum_{d \in D} DR_{t,d} \tag{1.8}$$

$$CDR_t = \sum_{t=-60}^{t} \overline{DR_t} - \sum_{t=-60}^{-31} \overline{DR_t} \tag{1.9}$$

where DB and CS in Equation 1.6 are the prices of Dated Brent and the BFO crude spot approximation in interval t on trading day d, respectively. The cumulative directional returns (CDR_t) represent the gain attainable through directional trading during the event window.[16]

In order to address the inherent relationship between directional trading based on spot market information and the futures market price movement,[17] I apply additional tests that isolate the spurious correlation between the futures returns and the direction parameter, consistent with Ederington and Lee (1995, EL).[18] This is achieved by assigning $FIXDIR_{t,d} = 1$ if $(R_{-31,0} - R_t) > 0$, $FIXDIR_{t,d} = -1$ if $(R_{-31,0} - R_t) < 0$, and $FIXDIR_{t,d} = 0$ if $(R_{-31,0} - R_t) = 0$ for intervals within the event window, where $R_{-31,0}$ is defined as $log(DB_{0,d}/CS_{-31,d})$ and R_t is $log(CS_t/CS_{t-1})$. Hence, the directional parameter for interval t within the window is based on the sign of the spot return over the other 29 minutes of the Platts assessment.[19] For intervals [t_{-60} = 15:30, t_{-31} = 15:59] and [t_0 = 16:30, t_{+59} = 17:29] outside of the Platts Window, the direction parameter is determined as specified in Equation 1.6. The EL approach can be considered as a

[16] I remove the eight flat fixing days from the analysis since the zero returns would attenuate the averaged outcome on positive and negative fixing days. This makes no material difference to the results.

[17] The correlation coefficient of the close-to-close Brent futures returns and the close-to-close Platts Dated Brent returns based on prices at 16:30 London time amounts to 0.97. However, the coefficient of the correlation determined based on the sign of (i) the difference between futures prices at 16:30 and 16:00, and (ii) the difference between the Platts Dated Brent benchmark at 16:30 and the BFO crude spot price at 16:00 is considerably lower, at 0.53.

[18] I thank an anonymous reviewer for suggesting this approach.

[19] Under the standard directional measure, I test whether the futures return of interval t within the 30-minute window is correlated with the overall 30-minute spot direction. Given the close co-movement between the spot and futures markets, it may appear that the return in interval t is correlated with the spot direction; however, it is actually only correlated with the overall 30-minute futures return. Hence, in order to avoid this correlation with itself (since the interval return is part of the 30-minute return), I compute the direction for each interval t within the window using the sign of the spot return of the other 29 minutes.

conservative robustness test of the directional return measure.[20]

Figure 1.3 reports the directional ICE Brent Crude futures returns around the Platts benchmark assessment using the two directional parameters. In Table 1.2, I report the ICE Brent Crude futures returns in 10-minute pooled batches across the full window of investigation.[21] The returns associated with the two are referred to as *DR* and *EL30R* respectively.

The cumulative simple returns for Brent futures shown in Panel A of Table 1.2 illustrate the responsiveness of the futures market to the daily benchmark assessment. This is supported by significantly negative $\overline{SR_t}$ values during the 30-minute Platts Window shown in Panel A of Figure 1.3. In Panel B of Table 1.2 I report the directional returns attributable to a physical-market-informed futures trader. An immediate and significant directional return is observed with the start of the fixing (t_{-30}), a pattern that carries forward throughout the assessment process—all 10-minute intervals exhibit significance at the 1% level. Further, the $\overline{DR_t}$ of intervals during the final phase of the benchmark assessment are particularly pronounced, measuring on average 10.6 bps from 16:20 to 16:29. Following the benchmark assessment's end (t_0), the pattern in the directional returns is reversed and falls to zero. The returns for the other 10-minute batches outside the 30-minute assessment window are smaller in magnitude, mostly insignificant, and depict no discernible pattern.

The cumulative directional returns in Panel A of Figure 1.3 represent the hypothetical gains attainable through directional trading in Brent futures during the Platts Window. There is an important run-up in *CDR* instantly after the start of the fixing and prior to

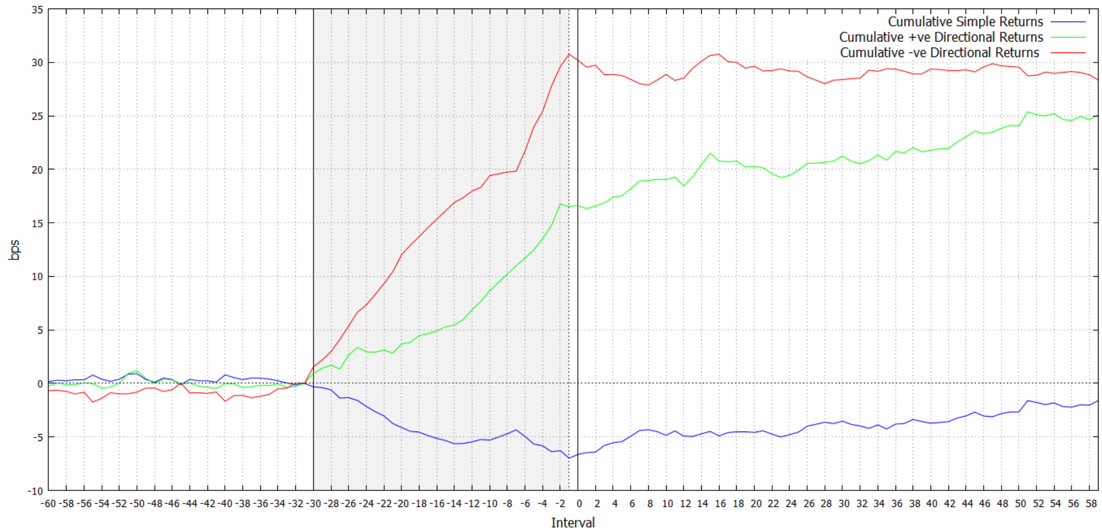
[20]Given that the last five minutes of the Dated Brent assessment are considered crucial (as described in Sub-section II.A and identified by the evolution of the volume and volatility in Figure 1.2), I implement a conservative third directional return measure. In this case, the FIXDIR is determined by the sign of the differential between the Dated Brent price and the BFO spot price five minutes before the assessment end. The unreported results are smaller in magnitude but consistent with those reported in Table 1.2.

[21]For parsimony I do not report the minute-by-minute results; however, the results are available on request.

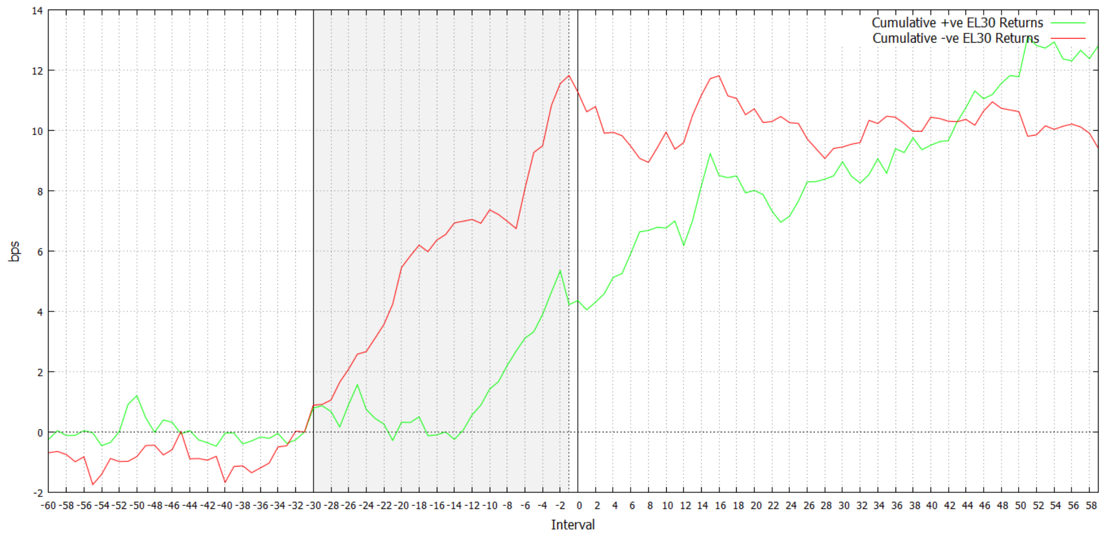
its end. As demonstrated in Panel A of Figure 1.3, the clear and continuous trend in directional futures returns during the event window suggests that the trading activity, such as spot-market-informed futures speculation or informed spot-futures arbitrage, leads to an adjustment of almost 24 bps on average. The trend in the Brent futures price in the 'right' direction prior to the end of the daily Platts Window amounts to 16.5 bps during positive assessments, and 30.8 bps during negative assessments. The steepening of the *CDR* curve from t_{-7} onwards underlines the importance of the final minutes of the Platts Window. This pattern is followed by a reversal on negative days, possibly due to overshooting in the market. However, on positive days a slight and continuous upward trend is observed.

Figure 1.3. Cumulative returns for ICE Brent Crude futures

(a) Cumulative returns



(b) Cumulative *EL30* returns



Notes: Panels A and B show the cumulative directional return measures using the standard directional fixing parameter and the EL-corrected 30-minute directional parameter respectively. The split into positive (+ve) and negative (−ve) assessment days is determined for each panel based on $FIXDIR_{t,d}$ described in Equation 1.6. All return measures are reported in bps (1 bps = 0.01%). The shaded area indicates the event window from fixing start (t_{-30}) to fixing end (t_{-1}) [16:00:00, 16:29:59]. The vertical black line marks the interval following the Platts Dated Brent assessment end: t_0 [16:30:00, 16:30:59].

Panel C of Table 1.2 reports the returns based on the EL-corrected 30-minute directional sign (*EL30R*), designed to avoid the expected spurious correlation between the return in interval t and the spot direction on day d during the Platts Window. Under this conservative measure, the direction of interval t is based on the sign of the spot return over the other 29 minutes. While the *EL30R* results are smaller in magnitude, the estimates remain statistically significant during all three 10-minute batches, culminating in an average return of eight bps (Panel C of Table 1.2). Consistent with earlier results, Panel B of Figure 1.3 shows that negative Platts assessment days experience stronger cumulative directional returns, while the movement is less pronounced on positive assessment days.[22]

Overall, the two directional return measures yield consistent results, albeit at different magnitudes, implying that there is an idiosyncratic information component in the spot market, enabling a directional pattern to emerge in the futures market during the Platts Dated Brent assessment. The findings suggest that, theoretically, a futures trader with spot market information could make an average profit of between 8 bps and 24 bps during the 30-minute assessment window.

[22]Since the EL direction parameter equals the standard fixing direction for intervals outside the event window, the *DR* and *EL30R* during the pre-event and post-event windows are identical in Panels B and C.

Table 1.2. Return measures by batches for ICE Brent Crude futures

10 mins				Panel A			Panel B			Panel C		
				Avg Simple Returns			Avg Directional Returns			Avg EL30 Returns		
From (t_i)	*To* (t_i)	*From* (*Time*)	*To* (*Time*)	*SR*	*Sign*	*t-value*	*DR*	*Sign*	*t-value*	*EL30R*	*Sign*	*t-value*
-60	-51	15:30	15:39	-0.60		-0.57	1.02		0.96	1.02		0.96
-50	-41	15:40	15:49	-0.70		-1.00	-0.60		-0.83	-0.60		-0.83
-40	-31	15:50	15:59	-0.10		-0.16	0.64		0.83	0.64		0.83
-30	-21	16:00	16:09	-3.70	***	-4.55	6.60	***	8.14	1.97	**	2.10
-20	-11	16:10	16:19	-1.50	**	-2.11	6.37	***	9.20	1.93	**	2.30
-10	-1	16:20	16:29	-1.70	**	-1.98	10.60	***	12.97	4.11	***	4.16
0	9	16:30	16:39	2.47	***	3.23	0.10		0.12	0.10		0.12
10	19	16:40	16:49	-0.02		-0.03	1.12		1.61	1.12		1.61
20	29	16:50	16:59	0.77		1.10	-0.30		-0.39	-0.30		-0.39
30	39	17:00	17:09	0.20		0.33	0.71		1.19	0.71		1.19
40	49	17:10	17:19	0.89		1.40	1.59	**	2.50	1.59	**	2.50
50	59	17:20	17:29	1.08	*	1.90	-0.10		-0.23	-0.10		-0.23

Notes: This table reports the results of the average return measures in 10-minute batches. Panels A, B, and C present the results for the average simple returns, the average directional returns and the EL-corrected 30-minute directional returns respectively. All return measures are reported in bps (1 bps = 0.01%). The t-value is the statistic of a one sample t-test of the mean being equal to zero. *, **, and *** correspond to statistical significance at 10%, 5%, and 1% levels respectively. Sample period is 09.01.2012–31.03.2016. 'From' and 'To' timestamps represent interval start times. The two single horizontal black lines represent the Platts Dated Brent fixing start and fixing end. The interval following the Platts Dated Brent assessment end is t_0 [16:30:00, 16:30:59] London local time.

C. *Trade order imbalance around the Dated Brent benchmark assessment*

In order to further substantiate the view that informed trading drives directional trading in the Brent futures market, I next examine the evolution of trade order imbalance around the assessment window. Order imbalance is a well-established measure in the literature for identifying patterns of informed trading (e.g., Bernile et al., 2016). I apply the Lee and Ready (1991) trade classification algorithm to identify Brent futures trades as either buyer- or seller-initiated. Trades above the prevailing midpoint are classified as buys, and those below the prevailing midpoint are deemed to be sells.[23] I measure order imbalance as follows:

$$DOIB\#_{t,d} = \frac{(\#B_{t,d} - \#S_{t,d}) \times FIXDIR_{t,d}}{\#B_{t,d} + \#S_{t,d}} \tag{1.10}$$

$$\overline{DOIB\#_t} = \frac{1}{D} \sum_{d \in D} DOIB\#_{t,d} \tag{1.11}$$

where $\#B_{t,d}$ is the aggregated number of buyer-initiated transactions in interval t, and $\#S_{t,d}$ the aggregated number of seller-initiated transactions in interval t (Chordia et al., 2008). I sign the Brent futures order imbalance for each interval t by the fixing direction of that trading day d (Equation 1.10) to facilitate the identification of directional trading. I apply an additional specification of the direction parameter, as described in Sub-section IV.B (i.e., the EL-corrected direction parameter over the full 30-minute window). The *DOIB* measures adopt positive values if market participants trade in the

[23]In cases where the trade was executed exactly at the midpoint, I determine the direction based on the first preceding transaction that was executed at a different price, a practice also called the 'tick test' (Lee and Ready, 1991). Holden and Jacobsen (2014) report that the Lee and Ready (1991) trade classification algorithm is reasonably accurate (88%) in today's context of fast markets.

'right' direction, and negative values otherwise. If there is no evidence of consistent directional trading in the Brent futures contract, a random pattern should be observed. $\overline{DOIB\#_t}$ and $\overline{EL30\#_t}$ describe the values for interval t averaged across all trading days D. The results for the directional order imbalance by number of trades (#) are presented in Table 1.3.[24] I report the order imbalance results in 10-minute batches.

Overall, the results largely mirror the earlier directional return findings. The $\overline{DOIB\#_t}$ values in Panel A are typically statistically insignificant for intervals preceding the event window but show continuous and significant positive non-zero values during the Platts Window. The pattern is reversed following the completion of the assessment window. With mean values of 2.43% between 16:10 and 16:19, trades in the 'right' direction outweigh trades in the 'wrong' direction by several percentage points at their peak. In addition, and again in support of earlier findings, $\overline{DOIB\#_t}$ yields values of -1.62% (1% level of statistical significance) immediately after the end of the Dated Brent fixing, from 16:30 to 16:39. These values indicate a transaction pattern in the opposite direction to the fixing and are possibly driven by the reversal in positions of some participant groups following the end of the benchmark assessment. This could also be the consequence of the crowding out of informed traders by noise/uninformed traders, as the former abandon their positions upon earning abnormal returns at the end of the assessment period.

[24]The results for the order imbalance measure by dollar value ($) are identical.

Table 1.3. Order imbalance measures by batches for ICE Brent Crude futures

10 mins				Panel A			Panel B		
				Avg DOIB (#)			Avg EL30 DOIB (#)		
From (t_i)	*To* (t_i)	*From* *(Time)*	*To* *(Time)*	*DOIB#*	*Sign*	*t-value*	*EL30#*	*Sign*	*t-value*
-60	-51	15:30	15:39	0.49		1.03	0.49		1.03
-50	-41	15:40	15:49	-0.96	**	-2.01	-0.96	**	-2.01
-40	-31	15:50	15:59	-0.32		-0.66	-0.32		-0.66
-30	-21	16:00	16:09	1.79	***	4.07	0.88	**	1.99
-20	-11	16:10	16:19	2.43	***	5.05	1.53	***	3.11
-10	-1	16:20	16:29	1.94	***	5.07	0.91	**	2.42
0	9	16:30	16:39	-1.62	***	-3.78	-1.62	***	-3.78
10	19	16:40	16:49	-0.91	*	-1.68	-0.91	*	-1.68
20	29	16:50	16:59	-1.10	**	-1.99	-1.10	**	-1.99
30	39	17:00	17:09	-1.07	*	-1.82	-1.07	*	-1.82
40	49	17:10	17:19	-0.16		-0.28	-0.16		-0.28
50	59	17:20	17:29	-0.64		-1.13	-0.64		-1.13

Notes: This table reports the results of the average *DOIB* measures in 10-minute batches. Panels A and B present the results by number of trades (#) using the different specifications of the directional parameter as described in Sub-section IV.B. The measures are expressed in percentage terms (%). The t-value is the statistic of a one sample t-test of the mean being equal to zero. *, **, and *** correspond to statistical significance at 10%, 5%, and 1% levels respectively. Sample period is 09.01.2012–31.03.2016. 'From' and 'To' timestamps represent interval start times. The two single horizontal black lines represent the Platts Dated Brent fixing start and fixing end. The interval following the Platts Dated Brent assessment end is t_0 [16:30:00, 16:30:59] London local time.

Order imbalance results using the conservative EL-corrected direction sign are presented in Panel B of Table 1.3. The *EL30#* estimates show positive and highly significant order imbalance values, consistent with Panel A's estimates, although marginally lower in magnitude. The estimates for 16:00–16:09, 16:10–16:19, and 16:20–16:29 are 0.88, 1.53, and 0.91 respectively. Following the end of the assessment (16:30 to 17:29), I obtain significantly negative values, indicating an overbalance of trades in the opposite direction to the price movement during the Platts Window. The absence of a similar trading behavior outside of the event window supports the directional trading proposition that informed activity in the Brent futures market from 16:00 to 16:30 leads to an adjustment of the futures price in the direction of the benchmark outcome.

D. The arrival rate of informed traders

To substantiate the suggestion that the observed pattern is driven by informed trading, I estimate the probability of an informed trade (*PIN*) model (see Easley et al., 2002, 1996a, 1997, 1996b). The *PIN* model assumes that the trading process involving informed and liquidity traders and market makers iterates over multiple trading intervals. Four parameters determine this trading process: α, the probability that an information event occurs; δ, the probability of the former being a bad news event; μ, the arrival rate of informed traders; and ε, the arrival rate of uninformed traders. Assuming a Poisson-like distribution of trades, the model allows me to estimate each of the parameters of the Brent futures trading process by maximizing the following likelihood function:

$$
\begin{aligned}
L\big((B,S)|\theta\big) =&(1-\alpha)e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!} \\
&+\alpha\delta e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-(\mu+\varepsilon)T}\frac{\big[(\mu+\varepsilon)T\big]^S}{S!} \\
&+\alpha(1-\delta)e^{-(\mu+\varepsilon)T}\frac{\big[(\mu+\varepsilon)T\big]^B}{B!}e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!}
\end{aligned}
\tag{1.12}
$$

PIN is computed as

$$PIN = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon} \tag{1.13}$$

where B and S are the total number of buys and sells in interval t respectively. As in Sub-section IV.C, I use the Lee and Ready (1991) algorithm to identify trade initiation. Brent futures are characterized by high liquidity, and I therefore use minute-by-minute buys and sells as inputs to the model, and subsequently estimate the PIN of 10-minute batches on a daily basis (following Easley et al., 1996b, as in Equation 1.13). In a final step, I average the 10-minute batch results across all trading days D to obtain the final parameter estimates.

During the event window, a surge in the arrival rate of informed traders is observed, as shown in Panel A of Table 1.4. The arrival rate of informed traders (μ) rises from 161.61 at the start of the event window [16:00, 16:09], to 162.56 [16:10, 16:19] and reaches a peak of 287.43 immediately prior to the end of the Platts Window [16:20, 16:29]. During the last five minutes of the benchmark fixing period, the valuation of forward BFOE is taking place (see Institutional Details in Sub-section II.A) and this is arguably the most important phase of the Dated Brent assessment. This supports the conclusions drawn earlier with respect to the directional return and order imbalance estimates, and thus also sustains the postulation on directional trading. It now appears to be a reasonable conclusion that informed traders drive at least part of the price run-up in the direction of the Dated Brent fixing price. Nonetheless, the arrival rate of uninformed traders (ε) also increases from 99.71 at the start of the event window [16:00, 16:09], to 100.41 [16:10, 16:19], and peaks at 154.81 ahead of the benchmark assessment's end [16:20, 16:29]. These findings align with the results showing heightened futures volume during the Platts fixing period, as a lot of participants with varying interests and degrees of sophistication are coming to the market during a period of very high liquidity. Informed speculators rely on liquidity, and thus noise traders, to make profitable trades, and a well-functioning futures market is therefore characterized by the presence of both informed and uninformed traders (cf. Brunnermeier and Pedersen, 2009; Silber, 1981). The larger ε (154.81), combined with the reduced probability that an information event will occur (α) ahead of the assessment end (see α of 31.19% [16:20, 16:29]) has the consequence that the largely increased μ (287.43) does not translate into a higher level of *PIN* (21.75%). Hence, with a diverse mix of uninformed and informed traders in the market, the probability of a market maker being adversely selected remains roughly the same throughout the estimation and event window. The probability of information-based trading thus remains at a constant level throughout those periods (see *PIN* in Table 1.4). Informed traders can, potentially, profit from the high volumes and use the correspondingly high level of uninformed traders to camouflage their informed trading activity (e.g., Collin-Dufresne and Fos, 2016; Kyle, 1985). It is important to note that the sustained presence of uninformed traders in the market, even in the face of a potential increase in adverse selection risk, is critical to the price discovery process (see Glosten and Milgrom, 1985; Kyle, 1985).

Table 1.4. Probability of information-based trading by batches for ICE Brent Crude futures

10 mins				Panel A	Panel B	Panel C	Panel D	Panel E
From (t_i)	*To* (t_i)	*From* (*Time*)	*To* (*Time*)	Arrival of Informed Traders μ	Arrival of Uninformed Traders ε	Probability of Information Event α	Probability of Low Signal δ	Probability of Informed Trade PIN
-60	-51	15:30	15:39	178.27	108.09	35.62	49.30	23.16
-50	-41	15:40	15:49	149.45	91.37	36.86	50.47	23.28
-40	-31	15:50	15:59	145.31	87.27	37.16	51.59	23.01
-30	-21	16:00	16:09	161.61	99.71	37.50	51.76	22.85
-20	-11	16:10	16:19	162.56	100.41	38.18	52.53	23.24
-10	-1	16:20	16:29	287.43	154.81	31.19	52.18	21.75
0	9	16:30	16:39	221.04	114.79	30.92	49.47	22.54
10	19	16:40	16:49	137.53	73.38	37.81	49.05	25.40
20	29	16:50	16:59	120.68	61.70	38.20	49.79	26.40
30	39	17:00	17:09	121.03	60.86	36.79	51.73	25.81
40	49	17:10	17:19	111.04	52.79	37.37	51.02	26.53
50	59	17:20	17:29	104.19	50.26	37.49	50.30	26.59

Notes: This table reports the results of the average estimates of the parameter vector of the structural model in 10-minute batches. The parameters μ, ε, α, and δ refer to the arrival rate of informed traders, the arrival rate of uninformed traders, the probability of an information event occurring, and the probability of a low signal occurring respectively, per 10-minute batch and averaged across trading days D. *PIN* is computed daily by batch as in Equation 1.13, and then averaged across trading days D. The probability measures α, δ, and *PIN* are expressed in percentage terms (%). Minute-by-minute buys and sells serve as input to the structural model. Sample period is 09.01.2012–31.03.2016. 'From' and 'To' timestamps represent interval start times. The two single horizontal black lines represent the Platts Dated Brent fixing start and fixing end. The interval following the Platts Dated Brent assessment end is t_0 [16:30:00, 16:30:59] London local time.

E. Predictive co-movement analysis

Opportunities to capitalize on oil market information should be greater on days with pronounced benchmark price innovations, measured by the magnitude of the differential between the Platts Dated Brent price and the pre-assessment spot price. If there is any predictive value in market movements, one should observe futures trading (for arbitrage purposes or speculation) in the direction of the fix as the benchmark assessment evolves. In Table 1.5, consistent with Caminschi and Heaney (2014), I report the alignment between $FIXDIR_{t,d}$ and the change between the futures price in interval t and the pre-assessment futures price (at t_{-31}). I measure $FUTDIR_{t,d} = sign(F_{t,d} - F_{-31,d})$, over the 30 intervals making up the Platts Window. If $FIXDIR_{t,d} = FUTDIR_{t,d}$, alignment is established; the converse is true in the case of deviations. I condition on *small* or *large* assessment days, depending on whether the Dated Brent assessment magnitude on day d is below or above the median assessment magnitude over the full sample period. Subsequently, I examine whether the alignment rates of futures returns with the fixing directions are uniformly distributed for small and large Dated Brent assessments. If there is no value in the initial market movements, alignment for small and large innovation days should be equally likely.

The sub-samples consist of 528 large innovation days and 528 small innovation days. The baseline case considers the interval immediately preceding the start of the Dated Brent assessment (t_{-31}). Specifically, when the prediction of the fixing direction is based on returns in the futures market from 15:59 to 16:00, I find poor alignment. Futures returns only correctly identify the assessment direction 45.64% of the time. While proportions are different between large and small innovation days, chances remain poorer than a coin toss (42.80% versus 48.48%, respectively). Immediately after the start of the Dated Brent assessment (interval t_{-30}), the first minute's return in the futures market aligns with the spot fixing direction 51.89% of the time. Futures price movements are

56.44% accurate on large innovation days, and significantly different from small innovation days (47.35%). This pattern remains consistent throughout the Platts Window.

On small fixing days, futures returns have an above-average probability of being aligned with the fixing direction only five minutes (t_{-26}) after the assessment starts. On large innovation days, however, that probability has already amounted to approximately 61% by that time. Halfway through the assessment window, the probability has risen to 74% (t_{-15}), and it reaches 80% five minutes before the assessment period ends. On small fixing days, the probability that futures returns are correctly aligned with the fixing direction stays close to 50% for the majority of the assessment period, remains below 60% until 16:21 (t_{-9}), and does not surpass 67% until the end of the assessment period. Overall, the rate of increase in the probability of alignment is considerably slower on small fixing days.

The difference in the likelihood of correct alignment between small and large days is significant at the 1% level for nearly every interval. The fact that large innovation days achieve alignment faster may also imply there is less noise in the assessment process, and supports the presence of directional trading in the Brent futures market by informed participants.

Table 1.5. Co-movement of futures returns and the fixing direction

t_i	*To*	Magn	Deviate	Align	Prop	χ^2	t_i	*To*	Magn	Deviate	Align	Prop	χ^2
-31	15:59	Small	302	226	42.80%	3.44*	-15	16:15	Small	239	289	54.73%	43.87***
		Large	272	256	48.48%				Large	136	392	74.24%	
-30	16:00	Small	278	250	47.35%	8.74***	-14	16:16	Small	230	298	56.44%	32.14***
		Large	230	298	56.44%				Large	142	386	73.11%	
-29	16:01	Small	274	254	48.11%	4.38**	-13	16:17	Small	234	294	55.68%	39.96***
		Large	240	288	54.55%				Large	136	392	74.24%	
-28	16:02	Small	279	249	47.16%	10.26***	-12	16:18	Small	240	288	54.55%	52.32***
		Large	227	301	57.01%				Large	128	400	75.76%	
-27	16:03	Small	264	264	50.00%	8.8***	-11	16:19	Small	226	302	57.20%	41.71***
		Large	216	312	59.09%				Large	127	401	75.95%	
-26	16:04	Small	256	272	51.52%	8.86***	-10	16:20	Small	220	308	58.33%	39.73***
		Large	208	320	60.61%				Large	124	404	76.52%	
-25	16:05	Small	260	268	50.76%	15.81***	-9	16:21	Small	218	310	58.71%	40.88***
		Large	196	332	62.88%				Large	121	407	77.08%	
-24	16:06	Small	257	271	51.33%	13.44***	-8	16:22	Small	210	318	60.23%	32.39***
		Large	198	330	62.50%				Large	124	404	76.52%	
-23	16:07	Small	257	271	51.33%	13.44***	-7	16:23	Small	203	325	61.55%	34***
		Large	198	330	62.50%				Large	116	412	78.03%	
-22	16:08	Small	256	272	51.52%	14.89***	-6	16:24	Small	204	324	61.36%	35.58***
		Large	194	334	63.26%				Large	115	413	78.22%	
-21	16:09	Small	248	280	53.03%	13.59***	-5	16:25	Small	188	340	64.39%	32.54***
		Large	189	339	64.20%				Large	105	423	80.11%	
-20	16:10	Small	242	286	54.17%	17.25***	-4	16:26	Small	179	349	66.10%	32.11***
		Large	176	352	66.67%				Large	98	430	81.44%	
-19	16:11	Small	237	291	55.11%	24.58***	-3	16:27	Small	180	348	65.91%	39.32***
		Large	159	369	69.89%				Large	91	437	82.77%	
-18	16:12	Small	236	292	55.30%	31.69***	-2	16:28	Small	175	353	66.86%	40.31***
		Large	148	380	71.97%				Large	86	442	83.71%	
-17	16:13	Small	228	300	56.82%	29.28***	-1	16:29	Small	183	345	65.34%	48.02***
		Large	144	384	72.73%				Large	85	443	83.90%	
-16	16:14	Small	235	293	55.49%	37.32***	0	16:30	Small	173	355	67.23%	43.88***
		Large	140	388	73.48%				Large	81	447	84.66%	

Notes: This table reports the results of the alignment of the futures return with the Dated Brent assessment direction. t_i represents interval cut-offs. 'To' timestamps represent interval start times. Magnitude is assessed as $abs(log(DB_{0,d}/CS_{-31,d}))$. *Large* (*Small*) days are days with a Dated Brent assessment magnitude above or equal to (below) the median assessment magnitude. $FIXDIR_{t,d} = sign(DB_{0,d} - CS_{-31,d})$ as described in Equation 1.6. $FUTDIR_{t,d} = sign(F_{t,d} - F_{-31,d})$, where $F_{t,d}$ is the Brent futures price at the end of cut-off interval t, and $F_{-31,d}$ is the Brent futures price immediately preceding the start of the assessment window. For the special baseline case of interval t_{-31}, $FUTDIR_{-31,d} = sign(F_{-31,d} - F_{-32,d})$. *Align* (*Deviate*) is the count of days where $FIXDIR_{t,d} = FUTDIR_{t,d}$ ($FIXDIR_{t,d} \neq FUTDIR_{t,d}$) for the cut-off interval in question. All proportions are calculated as the ratio of *Align / (Deviate + Align)*, and are expressed in percentage terms (%). χ^2 reports the chi-squared test statistic of the contingency table formed by *Large, Small, Align*, and *Deviate*. *, **, and *** correspond to statistical significance at 10%, 5%, and 1% levels respectively. Sample period is 09.01.2012–31.03.2016. The interval preceding the Platts Dated Brent assessment start is t_{-31} [15:59:00, 15:59:59] London local time. The interval following the Platts Dated Brent assessment end is t_0 [16:30:00, 16:30:59] London local time.

F. Multivariate regression analysis

In this section, I test the robustness of my findings concerning the Dated Brent price assessment carried out by Platts, within a multivariate framework. I estimate the following regression models using the data sample of minute-by-minute intervals:

$$
\begin{aligned}
DV_{t,d} = \alpha &+ \beta_1 EVENT_{t,d} + \beta_2 POST_{t,d} + \beta_3 r_{VIX_{t,d}} \\
&+ \beta_4 r_{SP500_{t,d}} + \beta_5 r_{USDEUR_{t,d}} + \beta_6 r_{GOLD_{t,d}} + \beta_7 r_{SPOT_{t,d}} \\
&+ \beta_8 r_{MINING_{t,d}} + \beta_9 r_{OILGAS_{t,d}} + \beta_{10} ENERGY_{t,d} + \beta_{11} ECON_{t,d} \\
&+ \beta_{12} EXP_{t,d} + \beta_{13} SUR_{t,d} + \beta_{14} SENT_{t,d} + \beta_{15} CONTANGO_{t,d} \\
&+ \varepsilon_{t,d}
\end{aligned}
\tag{1.14}
$$

where the dependent variable (DV) corresponds to the directional return or order imbalance measure. $EVENT$ is a dummy variable equaling 1 during the Dated Brent benchmark assessment and 0 otherwise; it captures whether or not the directional trading effect during the event window persists after controlling for other possible drivers. $POST$ equals 1 during the post-event window and 0 otherwise. The directional log return on the S&P 500 volatility index (*VIX*), the S&P 500 stock index (*SP500*), the *USDEUR* spot exchange rate, and spot *Gold*, are included due to interrelations with the oil market evidenced in previous literature (e.g, Fan and Xu, 2011). $SPOT$ is the directional log return of the arithmetic average of the Thomson Reuters oil spot and swap prices. The directional log returns on the FTSE 350 mining sector (*MINING*) and the oil and gas sector (*OILGAS*) are included to control for price movements of related commodity firms. $ENERGY$ and $ECON$ equal 1 on days with important energy market or economic information releases, respectively, and 0 otherwise.[25] EXP equals 1 on ICE Brent Crude

[25] The calendar is taken from Bloomberg for all G8 countries and includes monetary, trade, labor, services, industrial, housing, purchasing, and governmental events and publications for the $ECON$ dummy. The $ENERGY$ dummy includes events such as the publication of the US Energy Information Administration (EIA) Weekly Petroleum Status Report and the EIA Natural Gas

futures expiry days, and 0 otherwise. The *SUR* indicator captures differences in the futures market on days with surprise Dated Brent price announcements, equaling 1 on such days and 0 otherwise. A surprise announcement is defined as a daily difference belonging to the top or bottom decile of all differentials between the published Dated Brent price and the pre-assessment spot price. The sentiment indicator (*SENT*) is 1 on days with a positive fixing direction, and 0 on days with a negative fixing direction. *CONTANGO* is a dummy variable that takes the value 1 on days when the structure of the Brent futures contract is in contango and 0 on days when it is in backwardation; this variable is included to control for the trend in oil prices. The sample contains 527 positive fixing days, 521 negative fixing days, and 8 flat days.

Table 1.6 reports the multiple regression estimates. There are several estimates of interest in light of earlier findings in this paper. Firstly, the *EVENT* dummy is significantly different from zero, and positive relative to the estimation window at the 1% level, even after controlling for numerous possible confounding effects. This abnormal return pattern suggests that trading behavior during the unfolding of the Platts Dated Brent benchmark assessment is indeed driven by directional trading activity. The *POST* dummy is insignificant in both panels, suggesting that trading activity is not different to the pre-event window following the end of the assessment.

I find that a positive relationship exists between the directional Brent futures returns and order imbalances and the S&P 500 stock index and spot gold returns. Moreover, a negative relationship is observed between the *USDEUR* exchange rate and Brent futures. These findings are broadly consistent with the existing literature on the interdependencies between oil, equities, gold, and the dollar (e.g., Fan and Xu, 2011; Narayan et al., 2010; Zhang et al., 2008). Furthermore, I find that positive interrelations exist between

Storage Change. Filters are applied to the releases in order to capture those of very high market relevance only. The recent intraday event study by Gu and Kurov (2018) provides evidence of early-informed trading in natural gas futures ahead of the release of the EIA Weekly Natural Gas Storage Report.

Table 1.6. Regressions of returns and order imbalance on control variables

	Panel A			Panel B		
	Directional Returns			Directional Order Imbalance (#)		
Variable	*Coeff*	*Sign*	*t-value*	*Coeff*	*Sign*	*t-value*
Intercept	-3.31E-06		-0.44	6.39E-03	**	2.26
EVENT	6.67E-05	***	9.96	1.38E-02	***	5.50
POST	2.94E-04		0.35	-3.76E-02		-0.12
VIX	3.33E-03	**	2.07	-5.36E-01		-0.88
SP500	3.46E-01	***	20.79	6.80E+01	***	10.87
USDEUR	-7.56E-02	***	-4.94	-5.32E+01	***	-9.29
GOLD	1.49E-01	***	16.58	3.20E+01	***	9.50
SPOT	-7.88E-03		-0.54	4.41E+00		0.81
MINING	8.28E-02	***	11.68	6.30E+00	**	2.37
OILGAS	5.44E-01	***	57.42	3.88E+01	***	10.92
ENERGY	7.60E-06		1.07	2.50E-03		0.94
ECON	-1.91E-06		-0.28	-4.65E-03	*	-1.82
EXP	-1.22E-05		-0.69	5.44E-03		0.82
SUR	4.80E-05	***	5.78	5.53E-03	*	1.77
SENT	-3.15E-05	***	-4.68	-1.52E-02	***	-6.02
CONTANGO	2.55E-05	***	3.71	1.08E-03		0.42

Notes: This table reports the results of the ordinary least squares (OLS) regressions of the dependent variables (*DR, DOIB#*) on several control variables over the total window of investigation. Panels A and B present the regression results for *DR* and *DOIB#* respectively. The independent variables account for different effects: *EVENT* adopts the value 1 during the Dated Brent benchmark assessment window and 0 otherwise; *POST* adopts the value 1 during the post-event window and 0 otherwise; *VIX*, *SP500*, *USDEUR*, and *GOLD* are the directional log returns on the S&P 500 volatility index, the S&P 500 stock index, the spot exchange rate between the USD and the EUR, and spot gold respectively. *SPOT* is the directional log return on the arithmetic average of Thomson Reuters oil spot and swap prices and serves as model for light crude spot oil. *MINING* and *OILGAS* are the directional log returns on the FTSE 350 mining sector and oil and gas sector respectively. *ENERGY* and *ECON* adopt the value 1 on days with an important energy market or economic information release and 0 otherwise. *EXP* adopts the value 1 on ICE Brent Crude futures expiry days and 0 otherwise. *SUR* adopts the value 1 for surprise Dated Brent fixings, defined as being in the top or bottom decile, and 0 otherwise. *SENT* is an indicator adopting the value 1 for days with a positive spot fixing direction and 0 for days with a negative spot fixing direction. *CONTANGO* adopts the value 1 or 0 on days where the Brent futures market is in contango or backwardation, based on the respective Bloomberg metric, controlling for the trend in oil prices. *, **, and *** correspond to statistical significance at 10%, 5%, and 1% levels respectively. Sample period is 09.01.2012–31.03.2016.

the dependent variables and the mining and oil and gas sector returns. Stock market volatility, as captured by *VIX*, positively influences directional returns, whereas no connection can be established for the order imbalance measure. The *SPOT* variable, modeling spot oil price movements, does not influence the directional Brent futures returns or order imbalances.[26]

The *ENERGY* and *ECON* dummy variables are insignificant in Panel A, demonstrating that the various energy and economic announcements do not impact the Brent futures directional returns over the window of investigation. However, in Panel B, the coefficient for economic announcement days is negative and statistically significant (10% level). In addition, contract rollover on expiry days of ICE Brent Crude futures has no statistically significant effect on either *DR* or *DOIB*. The regression results indicate that the directional returns and order imbalances are stronger on surprise Dated Brent announcement days (captured by the *SUR* variable). The negative and highly statistically significant *SENT* coefficient suggests that the directional futures returns behave differently on days with a positive Dated Brent fixing direction than on days with a negative fixing direction (refer to Appendix III for a more detailed discussion). Finally, structure, as proxied by *CONTANGO*, plays a role, as directional returns are significantly more marked on days where the oil market is in contango.

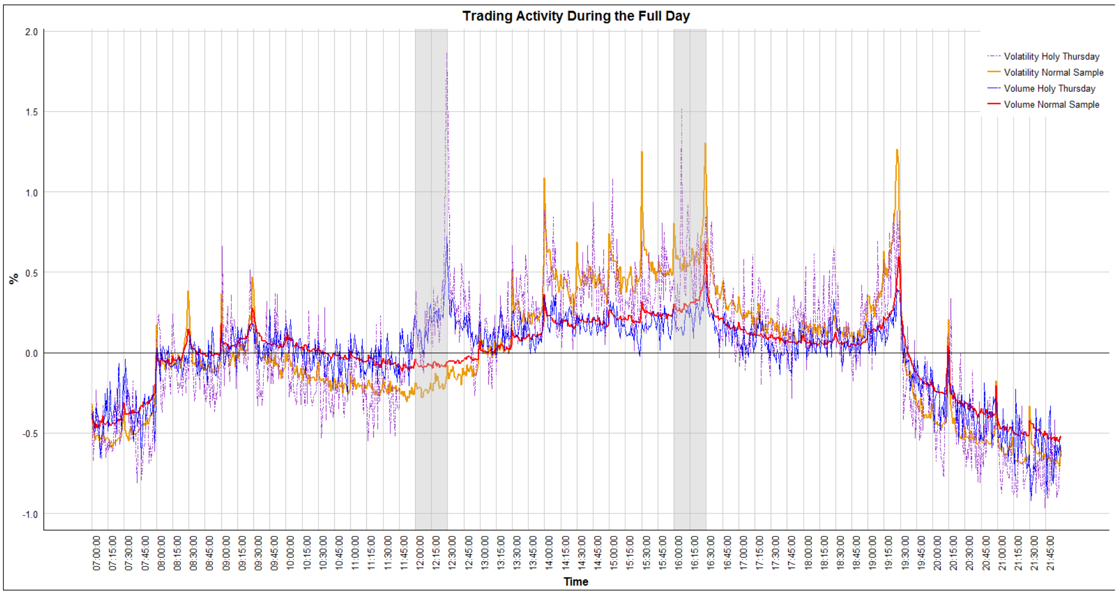
G. Early assessments

As with many important information releases, identification issues persist in the presence of confounding events. The typical assessment of the Platts Dated Brent coincides with the daily close of UK equity markets trading at 16:30 London time. However, on one day in the year this is not the case: *Holy Thursday.* On this day, two conditions are fulfilled that permit the disentangling of the effects of the equity market close on trading behavior in the oil derivatives market: (i) the benchmark assessment is conducted early and ends at 12:30 London time, and (ii) UK equity and Brent futures trading continues

[26] I attempt to control for other specific spot oil products such as the Dated Brent to Frontline Brent Futures contract, EFP contracts, or North Sea spot grade differentials. However, my efforts are constrained by various factors such as the unavailability of data, data restrictions, or the illiquidity of products.

as usual. I identify seven relevant days,[27] repeat the analysis, and compare it to the full-sample results to address the identification concerns. Figure 1.4 compares the volume and volatility for Holy Thursday, each year from 2010 to 2016, providing evidence that there is an increase in volume and volatility during the half hour before 12:30, with no comparable intensification in trading activity at 16:30.

Figure 1.4. Full day trading activity on normal and 'early assessment' days



Notes: This figure shows the development of volume and volatility on days with a 16:30 Dated Brent assessment (referred to as 'normal sample' days) and on days with a 12:30 Dated Brent assessment (referred to as 'Holy Thursdays'). Volume is computed as the log volume during interval t on trading day d, averaged across trading days D. Volatility is computed as the standard deviation of one-second returns within each one-minute interval t on trading day d, averaged across trading days D. The time series are demeaned and reported as percentage (%) increase/decrease relative to the daily mean. The shaded areas mark the period from 12:00 to 12:30 and 16:00 to 16:30 respectively. The normal sample consists of 1,056 days, while the Holy Thursday sample comprises 7 days from 2010 to 2016. The latter includes 2 out-of-sample days, to increase the sample size and smooth the series, without changing the results.

At the same time, for normal assessment days, there is no discernible pattern in volume or volatility around 12:30. Moreover, market opening or closing times of other major trading hubs cannot explain the 12:30 spike on Holy Thursdays. Hence, when the Platts

[27] I am grateful to Platts for providing data on these dates for an extended period and thank an anonymous reviewer for pointing me in this direction. The Platts Holiday Schedule, available online, allows me to confirm that the early assessment on Holy Thursday started in 2010. The inclusion of two out-of-sample days increases the sample size.

assessment deviates from its usual schedule, I observe a shift in the trading activity of the Brent futures market that coincides with the alternate assessment times. The pattern in directional returns is also consistent with the results, albeit not statistically significant.

Figure 1.4 identifies additional increases in volume and volatility at other times of the day. Unsurprisingly, they also correspond to meaningful events, for example, the start of the Open Outcry for WTI futures at 08:00 CT (14:00 London time), the US market openings (14:30 London time corresponding to 09:30 in New York), and the daily settlement of Brent futures at 19:30 London time. Morning US economic announcements align with the early afternoon in London. Predictably, the EIA Weekly Petroleum Status Report, with a release time corresponding to 15:30 London time, also causes major volatility in the oil futures market.

V. Conclusion

This paper is the first to document the observed behavior of Brent futures prices and the trading pattern around the Dated Brent benchmark assessment operated by the PRA, Platts. This study comes at a time when the regulatory status of commodity benchmarks has shifted back into focus with the upcoming EU Benchmarks Regulation.

I report significantly enhanced ICE Brent Crude futures market activity and sensitivity during the benchmark assessment that is carried out from 16:00 to 16:30, as measured by trading volume and price volatility. Futures market activity is particularly pronounced between 16:25 and 16:30, an interval of strategic importance in the Platts assessment. The futures price experiences a marked run-up commencing with the start of the Dated Brent price assessment period, and is quickly followed by a price reversal after the benchmark price assessment ends. I find evidence consistent with informed directional trading contributing to the price adjustment of the Brent futures, in alignment with the Dated Brent benchmark outcome, during the unfolding of its assessment. Nevertheless, the Platts Window also attracts many uninformed participants during this period of heightened futures market activity, suggesting that they do not withdraw from the market when faced with high informed trading activity. The continued presence of uninformed participants is critical to the transfer of price-relevant information to the Brent futures market and is deserving of further research in the future. Over the full 30-minute assessment window, spot-market-informed futures traders can realize returns amounting to 24 bps on average, with 8 bps being the most conservative estimate. Directional trading may be driven by futures speculation or spot-futures arbitrage, the informational advantage for which is plausibly gained in the physical crude oil market. The results are robust to a range of controls aimed at addressing the correlation between the developing benchmark assessment and futures price movements on the one hand, and capturing the effects of confounding events on the other. Overall, the results present a consistent view that the physical oil assessment by Platts is of material importance to the paper oil market.

Two caveats apply to the interpretation of the results. Firstly, the documented pattern may be magnified by market dynamics, such as participants herding on common signals (e.g., futures market order flow). Secondly, some of the interrelatedness between the spot and futures markets could be explained by an established cointegration relationship, which I am unable to completely factor into the analysis due to the unavailability of intraday North Sea crude spot data. These limitations notwithstanding, the extensive nature of the analysis suggests that the Dated Brent assessment plays a pivotal role in the price discovery of Brent futures. This study, therefore, emphasizes the influence of physical commodity benchmarks on exchange-traded financial products.

2

Skin in the game: Resource proximity and price impact

Abstract

I devise a novel dataset by integrating over-the-counter oil forward trading with exchange-traded futures activity to investigate the intricate interactions between the two markets. I answer a longstanding open question and report evidence that, on an intraday basis, the futures market is the dominant information leader, but that the forward market impounds a non-negligible 20% of price innovations. Forwards are also less noisy. The futures leadership is in line with the theory and findings of Figuerola-Ferretti and Gonzalo (2010). Moreover, I use the forward market centrality of traders with substantial 'skin in the game' in the oil market as a proxy for fundamental supply and demand information. Forward trades by more central participants have a more significant price impact on the futures market of up to 15 bps over a 10-minute window.

JEL classification: G13, G23, L14, Q02, Q41.

Keywords: forwards, futures, network analysis, OTC markets, physical oil

I. Introduction

The financialization of commodity markets, often defined as financial investors driving prices via speculation, has been a contentious topic over the last decade. In the oil market, derivatives markets (paper oil) have evolved rapidly alongside the physical markets (spot oil or cash oil), and the two are inextricably linked. In the North Sea, the different physical and financial oil contracts are commonly known as the Brent Complex.[1] This study focuses on the physically settled forward Brent contracts (also called forward BFOE, an acronym for the North Sea Brent-Forties-Oseberg-Ekofisk oil fields) and the financially settled ICE Brent Crude futures contracts to answer open questions in the literature on the importance of both contracts for the determination of the efficient price of oil. Data constraints, such as the reliance on low-frequency physical oil price proxies by previous studies (see for example Kaufmann and Ullman, 2009; Liu et al., 2015), impair our understanding of the intraday price discovery process in the oil market to this day. The proprietary dataset obtained for this study allows me to analyze the intricate intraday over-the-counter (OTC) trading of physical oil, and the impact the latter has on oil derivatives.

The OTC trading of physical oil has high barriers to entry, requiring participants to receive and deliver crude oil. Hence, the market mainly attracts oil majors, such as BP, Chevron, ConocoPhillips, Shell, and Total, and commodity traders, for example Glencore, Mercuria, Phibro, Trafigura, and Vitol (see Barret, 2012a, for an extended list of market participants). In a Bloomberg article by Cheong et al. (2017), commodity trading companies argue that superior information is required to trade successfully in the oil market:

[1]Elements of the Brent Complex include physical crude oil cargoes and forward contracts, Contracts for Differences (CFDs, which are short-term swaps between elements of the complex), Exchange of Futures for Physicals (EFPs, which price the differential between futures and forwards), and many others.

> "The most valuable commodity out there is information, and the most useful information is the proprietary, critical information that you obtain from your own supply chain. You have to have skin in the game. You have to have access to assets, whether it's infrastructure, terminals, vessels or refineries."

Accordingly, not only are the major oil corporations heavily invested in the oil supply chain but commodity trading houses continuously increase their investments in infrastructure too. I hypothesize that the 'skin in the game' argument reflects the structure of the oil market, where participants in the physical market are informed, and their trading behavior impacts the futures market. Participants are intensively involved in physical trading for many reasons, but their activity is arguably often based on supply and demand fundamentals received from their upstream (exploration and production) or downstream (refining, processing, and distribution) business lines. Their trading activity therefore reasonably serves as a proxy for fundamental information. For example, many physical trading participants are also owners or operators of oil fields that are feeding into the major North Sea oil grades (so-called equity owners), run refineries, own vessels, or invest in pipelines. The idea that physical OTC trading reflects fundamental information and thus serves as a signal to futures markets aligns with the literature, as commercial companies may capitalize on their superior knowledge of physical market conditions to exploit informational frictions (Cheng and Xiong, 2014; Frino et al., 2016).

This paper is structured into three components. In a first step, I establish a cointegrating relationship between the forward and the futures markets, and then decompose their price series into permanent innovations and transitory effects in order to determine price leadership. In a second step, I take a closer look at the trading process in the forward market and why it is important for the oil price development. In a third step, I link the trading activity in the forward market, and the 'skin in the game' of its participants, to the revelation of fundamental information and its incorporation into the futures price.

With regards to the cointegration and information leadership between the physical and financial oil markets, I find that the futures market is the information leader and incorporates approximately 81% of innovations to the efficient oil price. Actually, it is the case that, during most of the day, the futures market is responsible for 100% of the price discovery. This is explained by the fact that the forward market is only active during a short period at the end of the trading day—from 16:25 to 16:30. This study, however, demonstrates that, as soon as the forward market becomes active, even during this short period of the day, it manages to claim a non-negligible 19% of the price discovery share in the oil market. These findings align with Figuerola-Ferretti and Gonzalo (2010), who explain the permanent-transitory decomposition between the spot and financial markets, and whose results also establish futures price leadership for non-ferrous metals.

The forward BFOE market is characterized by a core-periphery structure, with a selected few core traders dominating the trading activity. Participants in the periphery interact with each other occasionally but trade more intensely with the core participants, who appear to adopt the unofficial role of 'market makers'.[2] Addressing the 'skin in the game' argument above, I hypothesize that the trading activity of core forward BFOE participants conveys information to the financial oil market and therefore significantly impacts the Brent futures price. In accordance with this proposition, a more central forward trader, as determined by the weighted out-degree network centrality measure, has a more significant price impact on the futures market—up to 15 basis points (bps) over a 10-minute window. This reaction very likely corresponds to the impounding of fundamental information from the physical crude oil market, given that the dominant traders in the forward market have infrastructure stakes, investments, and connections

[2]In the context of this paper, I do not use the term 'market maker' in its traditional sense of an equity stock exchange liquidity provider. I use the term in the strict sense of the Platts methodology documents, where it refers to a trading participant in their system who provides a quote before a certain cut-off period. Please refer to the institutional details in Section II.

to the upstream and downstream crude oil supply chains.

I contribute to the literature by identifying the price discovery roles of both the futures and forward markets on an intraday level. I demonstrate that the futures market is unsurprisingly the information leader, but the physical market still plays an essential role in determining oil price developments. Second, I provide first-hand evidence on trading activity in the forward market, and on how the major participants in this market influence financial oil prices as well. I add to the debate on the financialization of oil and the information transmission between spot and futures, by showing that the proximity to the natural resource and oil infrastructure appears to provide physical market participants with fundamental information that is revealed via forward trading and subsequently incorporated into futures prices.

The financialization debate in the academic literature discusses how financial investors affect and potentially distort trading in commodity markets. The futures market performs two crucial roles: (i) risk sharing—commodity producers hedge their price risk in the futures market for which speculators provide liquidity; and (ii) information discovery—centralized futures trading supplements the decentralized spot trading in information discovery (Cheng and Xiong, 2014).

I focus on the price discovery role played by financially settled oil and physically settled oil. The intersection of the exchange-traded (ET) and OTC market structures of oil has been the subject of active debate for years (see Garbade and Silber, 1983). In the commodity literature, centralized futures trading is seen to facilitate information aggregation, in the sense of Grossman and Stiglitz (1980) and Hellwig (1980), by solving informational frictions arising from the complicated supply, demand, and inventory dynamics of the spot market (Cheng and Xiong, 2014). However, Sockin and Xiong (2015) argue with their model that noise in commodity futures trading can create confusion whether speculation or economic fundamentals are driving prices. Empirical evidence on price discovery is inconsistent (see Bekiros and Diks, 2008; Inci and Seyhun, 2017; Kaufmann and Ullman, 2009; Liu et al., 2015; Quan, 1992; Schwarz and Szakmary, 1994; Silvapulle and Moosa, 1999), with some reporting a unidirectional relationship from futures to spot or vice versa, others a bidirectional relationship. Most of the studies using higher-frequency data (daily), but suggest that futures prices lead the price discovery and influence the spot prices (see for example Figuerola-Ferretti and Gonzalo, 2010). The findings are not surprising given the superior futures liquidity due to contracts that are ET, financially settled, consist of smaller lot sizes, have lower transaction costs, and are not constrained by operational requirements to handle physical oil. However, most, if not all, of these studies focus on low-frequency data (daily or monthly) and use proxies (such as benchmarks) to account for the physical market, since OTC data on spot oil trading is difficult to obtain. The low-frequency characteristic is a significant shortcoming given that adjustments to shocks in these markets occur within minutes (see Inci and Seyhun, 2017).

In addition, numerous studies provide theoretical and empirical support for the assertion that commodity market financialization substantially impacts oil information discovery and price developments (see for example Basak and Pavlova, 2016; Büyükşahin and Robe, 2014; Cifarelli and Paladino, 2010; Henderson et al., 2015; Silvennoinen and Thorp, 2013; Singleton, 2013; Tang and Xiong, 2012). For instance, prices are driven by the large financial inflows into commodity futures from index investors, changes in hedge fund positions, or increased volatility and correlation with other financial indexes. Other studies endorse fundamental supply and demand as the driver of price developments (see for example Büyükşahin and Harris, 2011; Fattouh et al., 2013; Hamilton, 2009; Hamilton and Wu, 2015; Irwin and Sanders, 2011; Irwin et al., 2009; Juvenal and Petrella, 2015; Kilian, 2009; Kilian and Murphy, 2014; Knittel and Pindyck, 2016). They often reject the 'bubble claim' that prices are driven purely by speculation. Overall, Cheng and Xiong (2014) conclude that the financialization has altered commodity markets considerably.

This study investigates the financialization of oil from the information discovery perspective. The newly obtained dataset consists of the order book of OTC forward oil contracts traded on the Platts *eWindow* platform—the most popular and active market for physical North Sea crude oil. I integrate OTC forward order book data with ICE Brent Crude futures data from Thomson Reuters Tick History (TRTH) on an intraday frequency to analyze price discovery and test the 'skin in the game' hypothesis. I thereby try to distill the effect of fundamental physical oil market information on the futures market.

The remainder of this paper is organized as follows: the next section (II) describes the institutional background. Section III introduces the data and provides descriptive statistics of the forward and futures markets. Section IV presents the primary results on the price discovery of both oil contracts, trading networks, and the impact of forward transactions on the futures price. Section V concludes.

II. Institutional details

A. Platts' eWindow

Platts, the leading provider of reference prices in the energy markets, operates a system called the Editorial Window (eWindow) to assess the Dated Brent benchmark. The eWindow resembles OTC trading venue consisting of a real-time open order book that reveals bids, offers, and ensuing trades. It is where price discovery takes place in the physical oil market. Chapter 1 and Appendix A provide a more detailed description of the mechanism.

As described by Barret (2012a), the final 30 minutes of Platts' so-called Market on

Close (MOC) process, from 16:00 to 16:30, concentrate liquidity in the physical oil market. During the daily half-hour period, known as the Platts Window, Platts computes the Dated Brent benchmark price based on the combination of trading activity in three OTC products: (i) physical North Sea cargoes, (ii) short-term swaps between Dated Brent and Forward Brent (i.e., CFDs), and (iii) outright forward Brent (also called cash BFOE).

The interest in this study only lies in the last element, the cash BFOE contract, since it is used to trade long-term supply and demand and is the physical counterpart of the futures contract. Cash BFOE is, therefore, the most appropriate contract to focus on in the 'skin in the game' context. Moreover, because I study North Sea crude oil dynamics, I do not incorporate products from other markets into my analysis. Naturally, many factors, products, and markets globally contribute to oil price discovery but are outside the scope of this paper. In addition, Davis (2012) determines that the Platts Dated Brent benchmark prices approximately 67% of the global physical oil traded and one might argue that the trading activity of North Sea physical and financial oil reflects most of the information.

Trading in eWindow is organized and governed by Platts' rules. As such, one can either trade as a so-called 'market maker' or 'market taker'. To become a market maker during the half-hour Platts Window, a participant must indicate his interest to trade to Platts ahead of a cut-off period by submitting a new bid/offer. After the cut-off period, Platts accepts no new bids/offers, and only existing quotes can be amended.[3] However, so-called market takers can hit the bid or lift the offer of a market maker at any time. The cut-off time for cash BFOE is 16:25:00 and after that only existing quotes can be amended by the market makers. Bids/offers for the forwards can be changed until the close at 16:30:00. This five-minute phase is judged to be of critical importance for price

[3] Source: http://www.rusneftekhim.com/docs/crude_oil.pdf.

discovery in the physical oil market. After 16:30:00 all bids/offers that have not been acted upon during the Platts Window expire.[4]

While only a limited number of companies, mastering the operational requirements of trading physical oil, participate in trading via eWindow, a more substantial number of subscribers to Platts' fee-based Global Alert (PGA) real-time information service can follow the live physical trading activity and order-flow information (transactions, bids, asks). This is of importance to this paper, since it allows, for example, futures traders to gain insights into physical oil price developments.

It is important to note that physical oil trading can take place throughout the day as well. However, the MOC methodology has the advantage of promoting liquidity in an illiquid market, as it leads to a natural concentration of activity in a short period at the end of the day (Barret, 2012a). Typically, the vast majority of the daily forward quoting and trading activity is concentrated between 16:25:00 and 16:30:00 (quote amendments and trading) and some of it between 16:20:00 and 16:24:59 (quote submissions before the cut-off). Given that forwards are the physical counterparts of futures, which, however, trade throughout the day, I focus on the last five minutes of the window.

B. The forward market

The forward contract derives its specification from Dated Brent, commonly considered the spot price for a cargo of North Sea oil. Since January 2012, Dated Brent has reflected the price of a crude oil cargo with an assigned shipping date between 10 and 25 days ahead. Forward Brent contracts, in contrast, specify the month of loading but have no date yet assigned. The seller communicates the date to the buyer within 25 days of the delivery, and thus the contract is also called *25-day forward*. It follows that forward contract expiry is on day number five in a 30-day calendar month (with slight

[4]Information received during the *Platts Oil Methodology Explained* session at the *Platts London Oil & Energy Forum*.

deviations for longer or shorter months); for example, the May12 contract expired on 5 April 2012. After that, Jun12 would have been the active contract.[5] In February 2015, Platts extended the spot Dated Brent date range to 10-30 days ahead. This change means that the forward contract now expires on the last business day of the month following the month-ahead Dated Brent date range. For example, the May15 contract expired on 31 March 2015.[6]

Forward price changes need to be incremental (under normal market conditions from 1 ¢/barrel (bbl) to 3 ¢/bbl) and prices (denominated in USD [$]) must stand firm long enough to be acted upon by a counterparty, to ensure orderly price discovery.[7] Forward contracts can be traded up to three months ahead and are settled physically (Barret, 2012a). The minimum trade size for forward BFOE is a partial cargo of 100,000 bbl. The majority of quotes correspond to this size. Occasionally quotes contain a quantity of 200,000 bbl, and can go up to 600,000 bbl (corresponding to a full cargo). The minimum shipment size acts as barrier-to-entry to the market. Only a limited number of companies, mastering the operational and logistical requirements of trading physical oil, participate in trading via eWindow. The firms are also required to satisfy Platts' due diligence requirements.

[5] Until 5 April, the 10-25 spot date range falls within April; the forward contract is thus May. After 5 April, the 10-25 spot date falls within May, and the forward contract is thus June. See https://www.platts.com/IM.Platts.Content/MethodologyReferences/MethodologySpecs/25Day_Brent_Calendar.pdf.

[6] Until 31 March, the 10-30 spot date range falls within April; the forward contract is thus May. After 31 March, the 10-30 spot date falls within May, and the forward contract is thus June. See https://www.platts.com/IM.Platts.Content/MethodologyReferences/MethodologySpecs/faq-month-ahead-dated-brent.pdf and https://www.platts.com/IM.Platts.Content/MethodologyReferences/MethodologySpecs/Dated-Brent-Month-Ahead-Calendar.pdf.

[7] Source: https://www.platts.com/IM.Platts.Content/MethodologyReferences/MethodologySpecs/oil-timing-increment-guidelines.pdf and https://www.platts.com/IM.Platts.Content/MethodologyReferences/MethodologySpecs/Platts-Forward-Curve-Oil.pdf.

C. The futures market

ICE Brent Crude futures are traded on ICE Futures Europe (IFEU) and are listed for each month seven years forward. I sample only the front-month, closest-to-maturity futures contract and roll over to the next contract at expiry.[8] Futures and forward expiries did not align precisely before March 2016. This had to do with the assessment of the Dated Brent and the implications for the forward contract maturities, as explained in the previous section.

All Brent futures contract months up to and including February 2016 expired at the end of the business day preceding the 15$^{\text{th}}$ calendar day before the start of the next contract month. For example, the Feb16 contract expired on 14 January 2016. Starting with the March 2016 contract, Brent futures have expired on the final business day two months ahead of the contract month in question. Thus, the Mar16 contract expired on 29 January 2016.

Before March 2016, I match the front-month forward contract with the closest futures maturity at that time. For example, the Aug15 forward contract would be matched to the nearby Jul15 futures contract from 1 June 2015 to 15 June 2015 and then the nearby Aug15 futures contract until 30 June 2015. Since the March 2016 adjustment, the futures and forward expiries have aligned.

The contract size in the futures market is 1,000 bbl and thus considerably smaller than the contract size in the forward market. The currency denomination is USD ($) per bbl, and the minimum price increment is 1 ¢/bbl. The Brent futures are cash settled against the ICE Brent Index, which is computed based on forward market activity. Moreover, a close link to the physical market exists via the EFP contract which converts a Brent futures position into a physically deliverable forward contract. For these reasons, futures

[8]Using only the nearest-maturity contracts is consistent with the literature on commodity derivatives. This is mainly because the closest futures contract is typically the most liquid, whereas the longer-dated contracts are predominantly thinly traded.

and forward prices commonly converge at expiry.

III. Data

Full order book data on physical oil trading was acquired from S&P Global Platts. The data consist of message-by-message activity for Platts Cash BFOE partial cargoes, also known as BFOE forward contracts. The dataset includes multiple forward maturities/contract months. I determine and focus on the front-month contract and use the data to reconstruct the full order book from 3 January 2012 to 1 February 2017, which includes trading of the contract months Feb12 to Apr17. Message timestamps are in milliseconds and the time zone is Greenwich Mean Time (GMT). I aggregate the data at the second frequency and convert all timestamps to reflect London local time.[9]

All standard order book variables, such as time, price, and quantity, are recorded and messages are labeled with a unique identifier and a sequence number, allowing me to trace the order life cycle from inception to the final state. Importantly, the forward data also contain the trader identifiers. As such, the identity of the sender of each message is known. Moreover, for transactions, the buyer and seller are reported too. Finally, the directionality of a transaction, i.e., the passive side as well as the active side of the trade, can be determined.

At the same time, Brent futures data for the same date range are obtained from TRTH. The data also include all standard variables, including the last trade price, bid and ask prices, and volumes. I sample the futures data at the second interval with timestamps reflecting London local time. The futures data do not contain participant identifiers.

I clean and merge the datasets together to create one aggregated time series of both forward and futures prices, allowing me to track the developments in both markets.

[9] I account for British Summer Time (BST), starting on the last Sunday of March and ending on the last Sunday of October.

Given the particularities of the forward market, as described in the institutional details section, there are five minutes each day during which the forward market activity overlaps with that of the futures market. To account for the registration of interest mechanism of the Platts Window (with new submissions cut-off ahead of 16:25), the window of interest extends from 16:22 to 16:30.[10]

Although the Brent futures and forward markets are closely interlinked, their structures are quite distinct. For this reason, I provide some comparative descriptive statistics of the data at my disposal in Table 2.1. I focus on the front-month contracts.

First of all, 91% of the quoting activity in the forward market falls within the five minutes from 16:25 to 16:30. 7% falls within the period from 16:22 up until 16:25. The remaining activity occurs either before or after this. Nearly all quoted prices have a quantity of 100,000 bbl attached. Regarding trades, 100% execute for the minimum trade size of 100,000 bbl.

The requirements that must be fulfilled in order to trade in the forward market are, by nature, more restrictive than those for the futures market. Hence, the total number of participants in the forward market over the entire period of investigation amounts to 22.[11] Although I do not have participant information for the futures market, it is reasonable to assume that the number is far more significant. The average number of forward traders during each contract month is 10.46. On a daily basis, on average, only 3.70 traders participate in the front-month contract. The quoting activity of the five most active traders accounts for 53% of all quote submissions, while they make up 68% of the total number of executed transactions.[12]

[10] See Appendix IV for full details on the data-merging process. Moreover, there are days when Platts performs an early assessment and therefore the window of interest ranges from 12:22 to 12:30.

[11] This corresponds to the number of participants quoting in the market and differs from the 21 traders that completed transactions as reported later in this study.

[12] These results are not tabulated due to the need to guarantee the anonymity of the traders, consistent with the data provision license.

Table 2.1. Summary statistics

Quotes			Trades	
Time	*Observations*	%	*Observations*	%
16:25-16:30	76,166	91	4,553	100
16:22-16:25	5,616	7	-	-
before 16:22	445	1	-	-
after 16:30	1,470	2	3	0
Quantity	*Observations*	%	*Observations*	%
100 K bbl	83,658	100	4,556	100
200 K bbl	34	0	-	-
300 K bbl	1	0	-	-
400 K bbl	2	0	-	-
600 K bbl	2	0	-	-
Participants				
	Total	*per maturity*	*per day & maturity*	
Forwards	22	10.46	3.70	
Transactions				
	Trading days	*Total*	*per maturity*	*per day & maturity*
Forwards	1,070	4,556	72.32	4.26
Futures	1,319	3,627,935	57,586.27	2,750.52

Notes: This table reports the summary statistics for front-month forward and futures trading. For forward quotes, *Observations* count the messages recorded on the Platts platform including new quote submissions, changes, cancellations, and executions for each of the specified time windows as well as the contract sizes ranging from 100,000 bbl to 600,000 bbl. For forward trades, *Observations* count the number of executed transactions only for the same categories. *Total*, *per maturity*, and *per day and maturity* report the average number of forward participants over the full sample period, each contract month, and each trading day in a traded contract month respectively. *Trading days* reports the number of active trading days in both contracts, while *Total*, *per maturity*, and *per day and maturity* contrast the number of forward and futures transactions in the sample.

From 2012 to 2017, forwards traded on 1,070 days, while futures traded on 1,319 days. A total of 4,556 front-month forwards were traded, virtually all of which were traded between 16:25 to 16:30. This corresponds to 4.26 trades per day. Overall, each contract month traded 72.32 times on average. In the futures market, during the same period and five-minute window, a total of more than 3.6 million transactions were concluded, with a mean volume of 2.06, accounting for a transaction size of roughly 2,060 bbl (for parsimony this result is not tabulated here). This is significantly less than the 100,000 bbl transaction size in the forward market. On a daily basis, this corresponds to an average of 2,750.52 front-month futures transactions, or 57,586.27 per contract month.

IV. Empirical analysis

A. Price discovery: Does the forward market matter?

The methodology in this section is based on Baillie et al. (2002), Gonzalo and Granger (1995), Harris et al. (2002), Hasbrouck (1995), Lehmann (2002), Putniņš (2013), and Yan and Zivot (2010).

Following the notation and presentation in Baillie et al. (2002), two price series that are cointegrated $I(1)$ are denoted $Y_t = (y_{1t},\ y_{2t})'$ with an error correction term $z_t = \beta' Y_t = y_{1t} - y_{2t}$, and have a cointegrating vector $\beta = (1,\ -1)'$.

The information share (IS) and component share (CS) are both based on a vector error correction model (VECM) of the form

$$\Delta Y_t = \alpha \beta' Y_{t-1} + \sum_{j=1}^{k} A_j \Delta Y_{t-j} + e_t \tag{2.1}$$

where the error correction vector is α; the zero-mean and serially uncorrelated innovations are termed e_t, with Ω being their covariance matrix. The first right-hand-side element in Equation 2.1 expresses the long-term relationship, also called the equilibrium dynamics, and the second right-hand-side element represents the short-term relationship between the two price series, driven by noise (bid-ask bounces, inventory calibrations etc.).

$$\Omega = \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix} \tag{2.2}$$

Accordingly, σ_1^2 is the variance of e_{1t} and σ_2^2 of e_{2t}. ρ is the correlation between the innovations.

From Hasbrouck (1995), one can convert Equation 2.1 into the integrated vector moving average (VMA), as represented in Equation 2.3:

$$Y_t = \Psi(1)\sum_{s=1}^{t} e_s + \Psi^*(L)e_t \tag{2.3}$$

$\Psi^*(L)$ is a matrix polynomial with a lag operator, L. $\Psi(1)$, called the impact matrix, depicts the sum of the moving average coefficients, i.e., the cumulative impact of an innovation e_t on the price. Again, the first right-hand-side element represents the long-term price impact of an innovation, and the second expression is the transitory component, which does not have a permanent price impact. Due to the long-term impact having the same effect on both price series, the impact matrix has identical rows, denoted $\psi = (\psi_1, \psi_2)$ in the next equation:

$$Y_t = \iota\psi\Big(\sum_{s=1}^{t} e_s\Big) + \Psi^*(L)e_t \tag{2.4}$$

where ι is a column vector consisting of ones.

Hasbrouck (1995) shows that ψe_t is the common efficient price of the two series, also called the common factor component, impounded into prices due to information. There is a close link between Equation 2.4 and the Stock and Watson (1988) common trend:

$$Y_t = f_t + G_t \tag{2.5}$$

where the common factor component is denoted f_t and G_t is the transitory component.

Hasbrouck (1995) demonstrates that the information share of a market is the contribution of that market to the total variance of the efficient price innovations, $var(\psi e_t) =$

$\psi\Omega\psi'$. The computation for the Hasbrouck (1995) IS, identifying market i's contribution to price discovery, is therefore

$$IS_i = \frac{([\psi M]_i)^2}{\psi\Omega\psi'},\ i = 1, 2. \tag{2.6}$$

where M is a lower triangular matrix. Ω is only diagonal if price innovations across markets are uncorrelated. Because Ω is often not diagonal, the Cholesky factorization of $\Omega = MM'$ is used to deal with the significant correlation of the innovations, e_t, by attributing the covariance term to the first market, leading to an upper bound estimate of the IS_i.

$$M = \begin{pmatrix} m_{11} & 0 \\ m_{12} & m_{22} \end{pmatrix} = \begin{pmatrix} \sigma_1 & 0 \\ \rho\sigma_2 & \sigma_2(1-\rho^2)^{1/2} \end{pmatrix} \tag{2.7}$$

The common approach is, therefore, to change the order of the price series and repeat the process, and then take the average of the lower and upper bounds to determine the IS_i (see Baillie et al., 2002). Baillie et al. (2002) show that, the higher is the correlation, the greater is the divergence between the upper and lower bound estimates. The lower bound thereby represents only the price's contribution, while the upper bound also includes the contribution from the correlation with the second price.

Equation 2.5 leads to the CS estimation proposed by Booth et al. (1999), Chu et al. (1999), and Harris et al. (2002) based on the Gonzalo and Granger (1995) permanent-transitory decomposition. The latter show that $f_t = \Gamma Y_t$. Γ is the common factor coefficient and Baillie et al. (2002) demonstrate that it is the orthogonal to the error correction coefficients $\alpha'_\perp = (\gamma_1,\ \gamma_2)'$.

The CS for market i can thus be computed as

$$CS_i = \gamma_i = \frac{\alpha_{\perp,i}}{\alpha_{\perp,1} + \alpha_{\perp,2}},\ i = 1, 2. \tag{2.8}$$

or

$$CS_1 = \gamma_1 = \frac{\alpha_2}{\alpha_2 - \alpha_1},\ C2_2 = \gamma_2 = \frac{\alpha_1}{\alpha_1 - \alpha_2} \tag{2.9}$$

Equation 2.9 shows that, if $\alpha_i = 0$, all price discovery takes place in market i, as that market does not correct for a disequilibrium between the two price series (Yan and Zivot, 2010).

Lastly, I follow Yan and Zivot (2010) and Putniņš (2013) and calculate the information leadership share (ILS):

$$IL_1 = \left|\frac{IS_1}{IS_2}\frac{CS_2}{CS_1}\right|,\ IL_2 = \left|\frac{IS_2}{IS_1}\frac{CS_1}{CS_2}\right| \tag{2.10}$$

and

$$ILS_1 = \frac{IL_1}{IL_1 + IL_2},\ ILS_2 = \frac{IL_2}{IL_1 + IL_2} \tag{2.11}$$

The *ILS* reported in this paper is the average of ILS_1 and ILS_2. I use the *ILS* for the main inference, as Putniņš (2013) demonstrates that *IS* and *CS* diverge if the levels of noise in the two markets differ. Both metrics then measure a combination of price leadership and relative avoidance of noise. The *ILS*, however, provides a clean measure of price discovery leadership, as it cancels out the dependence on the noise component. I follow the definition in Putniņš (2013) and determine that a market is the information leader if its price is the first to reflect innovations in the fundamental value of the underlying.

I aggregate the data at the one-second frequency and do so to reduce the noise in the estimation of the price discovery measures. A higher sampling frequency leads the lower and upper bound estimations to be very close to each other. The contemporaneous correlation is negligible because the *IS* estimation can more accurately identify the sequence of the markets' responses to new information (see for example Hasbrouck, 1995, 2003; Tse, 2000).[13]

In the analysis, I determine the price discovery measures on a daily basis for each front-month contract (63 months from February 2012 to April 2017), and average across days and then months.[14] I only include days on which the futures and forward markets are cointegrated at the 75% confidence level or higher. I use the Akaike information criterion (AIC) test to determine the optimal number of lags.[15] The reason for selecting this more lenient confidence level is the paucity of forward quoting activity and therefore the difficulty in establishing cointegration at the usual levels. Based on this, in my sample, 466 trading days are cointegrated. The results are reported in Table 2.2 and show that price discovery takes place in both the futures and the forward markets.

Table 2.2. Price discovery measures

Statistic	ISFUT	ISFOW	CSFUT	CSFOW	ILSFUT	ILSFOW
Mean	0.66	0.34	0.48	0.52	0.81	0.19
Median	0.67	0.33	0.48	0.52	0.83	0.17
Min	0.19	0.12	0.19	0.35	0.41	0.01
Max	0.88	0.81	0.65	0.81	0.99	0.59
St. Dev.	0.13	0.13	0.10	0.10	0.11	0.11

Notes: This table reports the mean, median, min, max, and standard deviation of the futures information share, $ISFUT$, forward information share, $ISFOW$, futures component share, $CSFUT$, forward component share, $CSFOW$, futures information leadership share, $ILSFUT$, and forward information leadership share, $ILSFOW$, respectively. The reported values are computed on a daily basis using log prices and then averaged across days and months.

The average daily information share of the futures market ($ISFUT$) across contract months amounts to 66%, while the forward market ($ISFOW$) makes up the remaining

[13] I choose one-second intervals to minimize the computational power required to compute the price discovery measures. However, the conclusions remain unchanged if I use millisecond data.

[14] This averaging approach does not materially affect the reported means of the price discovery metrics. I do this to report meaningful minimum and maximum values by contract month. Due to the volatile nature of the price discovery estimations, daily minimum and maximum values would equal 0.01 and 0.99.

[15] I use the Trace cointegration rank test and obtain the critical values from Johansen (1995). This approach is not uncommon. For example, Figuerola-Ferretti and Gonzalo (2010) use the 80% confidence level to establish cointegration between copper futures and spot. The results are not materially affected by choosing a higher or even lower cut-off.

34%. This split is not surprising given that, proportionally, much fewer quotes and transactions take place in the forward market. Generally speaking, forwards are only active for five minutes a day. These five minutes coincide, however, with arguably the most crucial period of the trading day in the oil market. This is when the price assessment of the Platts Dated Brent benchmark is in full swing and the spot, as well as financial, oil market is unusually alert. I demonstrate this in Chapter 1.

Across contract months, the average daily component share shows a more even split between the two markets, indicating even that the forward market is leading, with the *CSFUT* accounting for 48% and the *CSFOW* for 52% of the price discovery. The results for *IS* and *CS* can differ substantially because the price series are affected by different noise levels. "*CS* values low noise relative to speed, *IS* values speed relative to low noise, and *ILS* values only speed" (Putniņš, 2013, p. 81).

The measure of interest is, therefore, the *ILS*, which cancels out the noise of the price series, as developed by Yan and Zivot (2010) and Putniņš (2013). The futures market dominates price discovery, accounting for an *ILSFUT* of 81%. Nonetheless, the *ILSFOW* still amounts to 19%, suggesting that the physical oil trading introduces innovations to the oil market on a regular basis. This finding indicates that the forward market might be slower in incorporating information but is much less noisy, leading to the 50-50 split between *CSFUT* and *CSFOW*. The result aligns with the fact that the forward-to-futures quote ratio is infinitesimal, as only a select few companies can participate in forward trading. These companies often have a direct interest in the physical oil market and close links to supply and demand fundamentals through their upstream and downstream business lines. Their activity is thus often motivated by commercial needs. The futures market, in contrast, with its many participants with diverse trading interests, is much noisier. For instance, financial investors regularly engage in speculation on future oil price movements without possessing superior information, in line with the theory on the financialization of commodity markets. However, after accounting for the differences in noise, the *ILS* confirms the *IS* result, suggesting that the futures market is the leader in reflecting innovations about the fundamental value of oil.

Table 2.3. Price discovery leadership

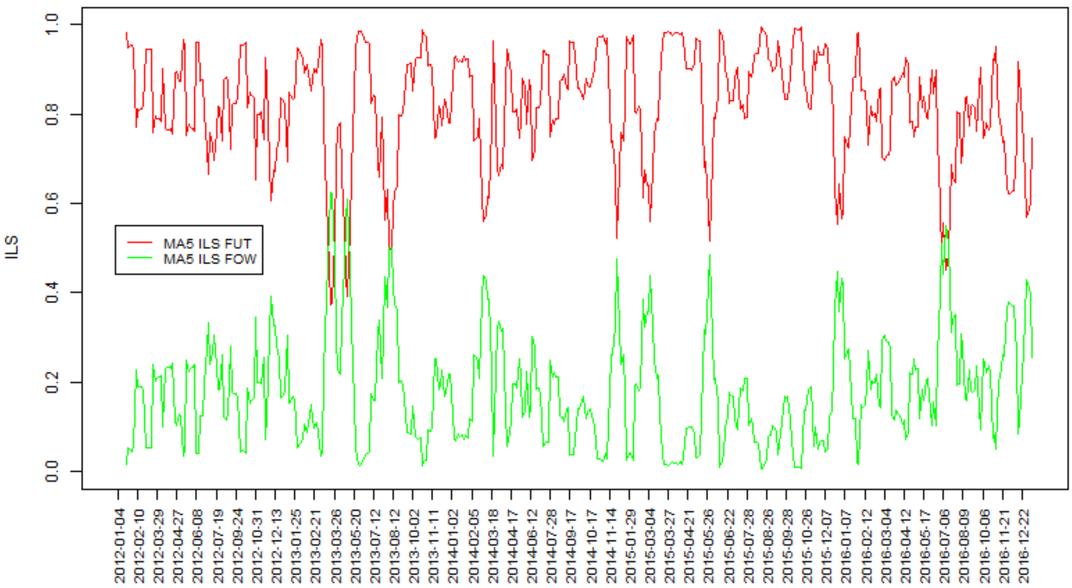
Leadership	n
Forward	61
Futures	405

Notes: This table reports the information leadership on a daily basis for all front-month contracts as measured by *ILS*. n indicates the number of information leadership days of the forward and futures contract respectively.

The three average daily price discovery measures by month are volatile, as indicated by standard deviations from 10% to 13%, as well as minimum and maximum *ILS* values that vary from just 1% to 59% in the case of the forward contract. Looking at this on a day-by-day basis, the futures contract is the uncontested information leader, guiding the forward contract on 405 out of 466 days (Table 2.3). Figure 2.1 further illustrates the consistent price leadership of the futures contract over time. Based on the five-day moving average, the *ILS* of the futures contract hovers between 60% and 100%, thereby claiming the majority of the price leadership. Nonetheless, the forward contract manages to claim more than 50% of the information leadership occasionally, even though its share also regularly drops down to 0%.

While the futures contract commonly leads the forward contract, informationally, the results demonstrate that the physical and financial oil markets closely interact with each other, and both contribute to the price discovery process on a daily basis. Interestingly, however, the forward price is less noisy and reflects nearly 20% of price innovations. The futures' informational dominance is likely driven by liquidity advantages because they are exchange-traded, financially settled, trade in smaller lot sizes, and have lower operational requirements and barriers to entry.

Figure 2.1. Price discovery over time



Notes: The y-axis depicts the *ILS* ranging from 0% to 100%. The x-axis shows the date range. The red line represents the five-day moving average of *ILSFUT*. The green line represents the five-day moving average of *ILSFOW*.

B. Networks in the physical oil market

Since many in-depth academic studies look at the oil futures market (see for example Liu et al., 2015) but acknowledge that, due to data constraints, little can be said about its physical counterpart, in this section I am the first to analyze OTC forward trading more closely.[16] The obtained data allow me to address the limitations of previous studies by applying techniques from social network analysis (SNA) that have recently found their way into financial economics, tackling questions such as how networks impact returns, price discovery, information diffusion, and OTC trading (see for example Di Maggio et al., 2017a,b; Hendershott et al., 2017; Li and Schürhoff, 2014; Munyan and Watugala,

[16]Several studies, such as those by Barret (2012a) and Fattouh (2011), conduct qualitative research on the interrelations between physical and financial oil, but no quantitative analysis has been undertaken.

2017; Ozsoylev et al., 2014).[17]

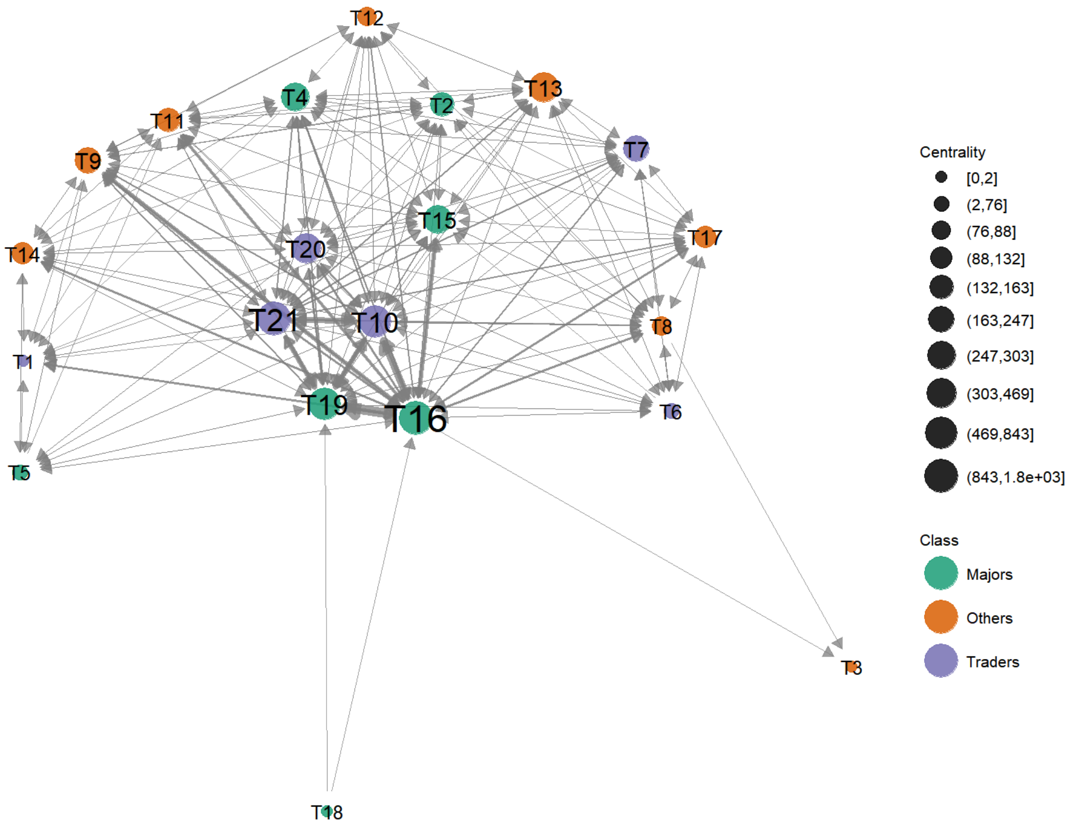
Figures 2.2 and 2.3 depict trading in the forward BFOE market. A node (circle) represents a trader, while the edge (arrow, line) that connects two traders represents an interaction (trade). The network figures are produced with the so-called Fruchterman-Reingold force-directed layout algorithm, which determines the optimal position of nodes by simulating attractive and repulsive forces to find an equilibrium state that minimizes the energy of the system.

Traders are assigned random numbers and are labeled *Ti*. Over the sample period there are 21 traders (which is different from the 22 quoting participants) in the cash BFOE market, and thus $i = 1, ..., 21$. These are mainly oil majors, commodity traders, and oil explorers, operators, and refiners, but the occasional financial institution is also represented. Additionally, many of these companies are so-called equity owners in North Sea oil grades, defined as owners or operators of oil fields that feed into one of the four BFOE oil grades. This fact speaks directly to the 'skin in the game' hypothesis, as some forward traders have direct infrastructure stakes in the underlying North Sea oil market.

The node size represents the centrality of the traders in the network and is determined by the weighted out-degree measure. The measure computes the number of outgoing edges of a node, counting interactions (including multiple interactions) with other nodes. Outgoing means that the arrow illustrates the directionality, i.e., the trade flow from the passive market maker's perspective. This is important because I want the centrality measure to reflect the relevance of the party that is revealing its intentions to either buy or sell. The edge weight thus determines the strength of the relationship, meaning the number of trades initiated by one trader and acted upon by the other trader. The weighted number of outgoing edges, therefore, represents the importance of a market maker in Platts' eWindow by also taking into account its market share. Without the

[17] For detailed surveys on the application of social networks in economic research, please refer to Easley and Kleinberg (2010), Goyal (2005), and Jackson (2005, 2008).

Figure 2.2. Forward BFOE trading network



Notes: This figure depicts the trading network in all forward BFOE contract months from February 2012 to April 2017 using the Fruchterman-Reingold algorithm. Arrow directionality is determined from the view of the passive buy/sell side of the trade—the so-called market maker according to Platts' terminology. A gray outgoing arrow therefore indicates trader *i* passively buying from or selling to another trader, or both. Edge weights outline the strength of the relationship. The node size and its respective text size indicate the centrality of the trader as measured by the weighted out-degree, i.e., the number of outgoing edges representing the importance of the trader as a market maker. The colors for *Majors*, *Others*, and *Traders* represent the classification into oil majors, commodity trading houses, and other business lines.

instigation of a market maker, no trade will take place. The centrality score, also depicted next to the figures, will be used as input to the regressions in the next section in the form of the *CENT* variable.[18] Based on the weighted out-degree measure, *T16* is the

[18]The network and centrality are determined based on all forward transactions in all contract months over the full sample period. The reason I use the entire sample period is that I aim to measure the importance of a market maker and his reputation as a major trading participant, established over time. I use transactions in all contract months to capture the overall standing of

most central trader, followed by *T21*, *T10*, and *T19*.

I surmise that the revealing of trading intentions by the main participants in the forward market impacts the prices in the futures market because it divulges information on the supply and demand of the actual physical resource. Although driven by a different intuition, the 'NYSE specialists literature' shows that trades with specialist participation have a higher immediate impact (see for example Hasbrouck and Sofianos, 1993). On the one hand, the futures market's reaction could stem from a mechanical relationship driven by the same participants trading in both the forward and futures markets and potentially triggering herding by other futures participants. On the other hand, trading strategies of futures traders observing physical market activity via Platts' PGA service (see Section II.A) could drive the price impact in the futures market. In both cases, the forward market serves as a signal to the futures market.

In Figure 2.2, the nodes are classified into oil majors, commodity trading houses, and other auxiliary businesses such as explorers, refiners, and financial companies. The core of the trading network is dominated by oil majors (green) and commodity traders (purple), while the periphery is made up of all three categories, but mainly auxiliary companies (orange). Within the core, oil majors have strong interactions amongst each other, as can be seen by the thick arrows between *T16* and *T19* and *T15* and *T16*. However, commodity traders occupy a central role in the market, being strongly connected with each other (*T21* with *T10*), but also with the oil majors in their network vicinity (*T21* with *T19* and *T16*, and *T10* with *T19* and *T16*). Moreover, a triangular relationship can be identified between *T10*, *T19*, and *T16*. Both majors and traders within the core have many trading interactions with less central participants too.

In Figure 2.3, the core-periphery relationship structure of the network is highlighted.

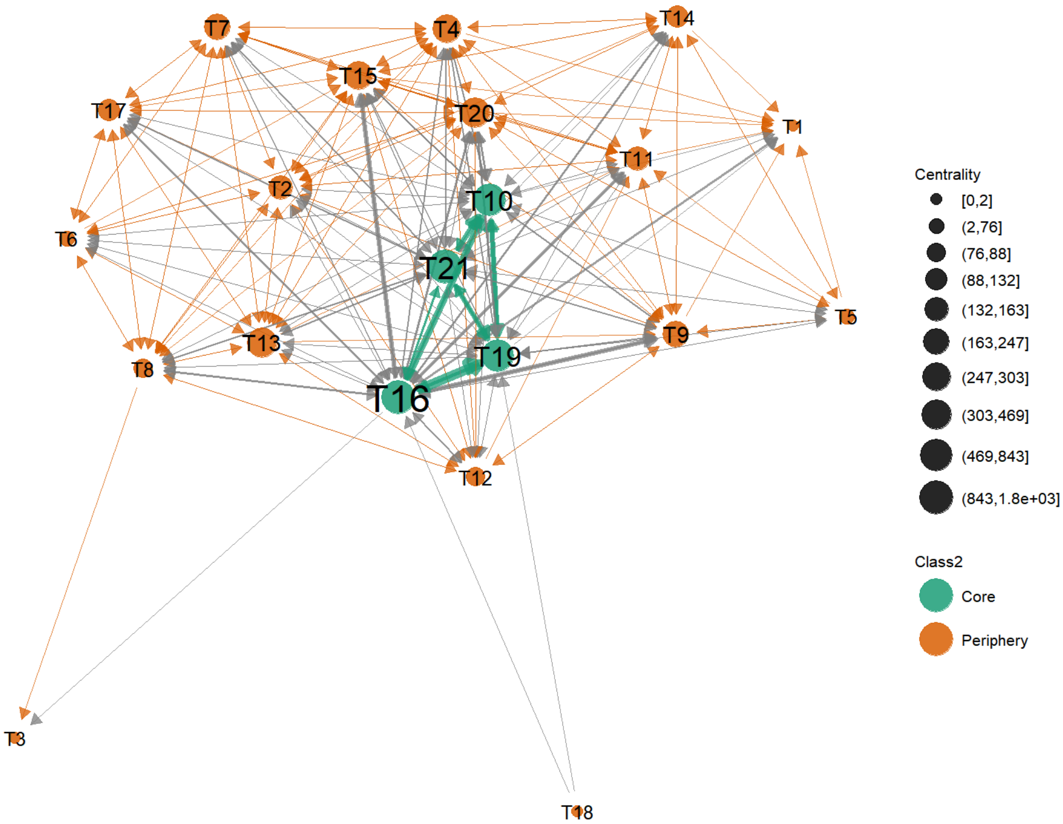
a trader in the market. In robustness tests I use (i) a compounded yearly centrality measure and (ii) only front-month forward trades instead, and find that the centrality ranking is remarkably persistent over time and that the results remain unchanged.

The green nodes (*T16*, *T21*, *T10*, and *T19*) build the core, and the rest of the traders are more or less peripheral. An edge adopts the color of the node if the interaction is between nodes of the same group (core-core or periphery-periphery interactions); an edge adopts the gray color for connections between nodes of different groups (core-periphery interactions). There are two 'outliers' that rarely interact with the market; trader *T3* that only has incoming edges, which means it only trades aggressively, and trader *T18* whose outgoing edges indicate its passive role in the market.

The figure underlines strong core-core trading relationships, as depicted by the thick green lines, indicating that core participants interact with each other frequently. Core-core interactions account for the majority of the trading activity. Periphery-periphery interactions are mostly weak. The thin orange arrows suggest intermittent trading in the outer perimeter of the network, indicating occasional rather than established trading relationships. There are some moderate core-periphery relationships, as illustrated by the medium-strength gray arrows between orange and green nodes. These connections imply that some peripheral participants regularly trade with the same core participants. Examples include the edges between *T15* and *T16*, *T9* and *T16*, and *T2* and *T21*.

Core dealers are often 'making the market', as indicated by the relatively strong outgoing gray arrows to the periphery (see for example the edges from *T16* to *T8*, *T9*, *T11*, *T14*, *T15*, and *T17*), suggesting that the core traders are passively buying from or selling to the periphery. Given the functioning of Platts' eWindow, the core traders thereby reveal their intentions, as passive bids and offers have to be posted before the 16:25:00 cut-off for cash BFOE. Quotes can subsequently be amended until 16:30:00, and other traders can hit the bid or lift the offer of a market maker. Many thin gray edges target core traders (notice the concentration of gray arrows around the core nodes), suggesting that core traders also aggressively buy from or sell to a wide range of peripheral traders.

Figure 2.3. Forward BFOE core-periphery interactions



Notes: This figure depicts the core-periphery structure of forward BFOE trading. Arrow directionality, edge weights, node and text sizes have the same meaning as in Figure 2.2. The color scheme represents the interaction of the *Core* and *Periphery*. An edge adopts the color of the node if the interaction is between nodes of the same group, or is gray for connections between nodes of different groups.

I hypothesize that the core-peripheral structure reflects the 'skin in the game' argument. The willingness and ability of traders to market make is closely linked to their business models and involvements in the upstream and downstream crude oil supply chains. More heavily invested traders have a better understanding of supply and demand levels (for example via their ownership or operation of oil fields and refineries) and have, therefore, better market making abilities and greater trading activities. This is then reflected in their centrality score. Hence, traders that are intricately involved in the physical trading of oil and often adopt the role of market makers are better informed about its fundamentals. The more central is a participant, the more telling is his trading activity for the financial oil market, leading to a price reaction from the futures market.

C. The impact of forward transactions on the futures market

This section tests the 'skin in the game' hypothesis and reports the main results of the study. Have transactions by more central forward traders a more pronounced impact on the price in the futures market? A likely source of price impact is fundamental supply and demand information, gained from involvement in upstream and downstream oil business lines, that is revealed to the futures market via forward trading.

To answer the research question, I compute the price impact of passively initiated forward buy and sell transactions on the futures market. This approach originates in the functioning of Platts' eWindow, where the so-called market makers reveal their intentions to buy or sell, as passive bids and offers have to be posted before the 16:25:00 cut-off for cash BFOE. Without this revelation of intentions, no trades will take place, as market takers can only aggressively hit or lift existing quotes. I am thus interested in the reaction of the futures market to the participants' divulged needs to buy or sell large quantities of crude oil. Transaction sizes in the forward market are very large (100,000 bbl) and comparable to equity block trades; I therefore adopt a similar methodology to the one established in that literature (see for example Anand et al., 2012; Chan and Lakonishok, 1993, 1995; Holthausen et al., 1987, 1990; Kraus and Stoll, 1972). I take every forward transaction and identify the futures price in the market at the time of the trade, as well as the futures prices before and after the trade.

The permanent effect (PE) is computed as

$$PE\,(\%) = ln\left(\frac{P_{post}}{P_{pre}}\right) * 100 \tag{2.12}$$

The total effect (TE) is defined as

$$TE\ (\%) = ln\left(\frac{P_t}{P_{pre}}\right) * 100 \tag{2.13}$$

Finally, I calculate the liquidity effect (LE) as

$$LE\ (\%) = ln\left(\frac{P_t}{P_{post}}\right) * 100 \tag{2.14}$$

where P_t is the futures price at the time, t, of the forward transaction. P_{pre} and P_{post} are the futures prices five minutes before and five minutes after the forward transaction respectively. I choose five-minute intervals because all forward transactions happen between 16:25:00 and 16:30:00, which is part of the Dated Brent benchmark assessment period, and I thus allow the futures price to adjust to the information introduced by physical OTC trading activity.[19]

In a second step I run the following regression specification:

$$DV_t = \alpha + \beta_1 CENT_i + \gamma' X_t + \epsilon_t \tag{2.15}$$

where DV_t is one of the three price impact measures (PE, TE, LE) assessing the effect of a forward transaction on the futures price. $CENT_i$ is the full-sample-period centrality of the forward trader i of the transaction in question, as explained in Section IV.B.[20] I follow the existing literature (see Aggarwal and Samwick, 1999; Li and Schürhoff, 2014; Milbourn, 2003) and use an empirical cumulative distribution function (ECDF) to normalize the weighted-outdegree centrality measure to the range [0 = least central; 1 = most central]. The ECDF transformation has the advantage of maintaining the original

[19]Hence, P_{pre} and P_{post} fall outside of the 16:25:00 to 16:30:00 window. Moreover, the results are robust to choosing different window lengths such as 10 minutes and 15 minutes.

[20] I conduct robustness tests computing centrality on a yearly compounded basis. The unchanged results can be found in Appendix VIII.

ordering of centrality and mitigating the biases introduced by skewness and outliers, while simplifying the economic interpretation of the centrality variable (Li and Schürhoff, 2014). As such, a one-unit increase in centrality corresponds to a trader improving from the least central, $CENT = 0$, to the most central, $CENT = 1$, position.[21] X_t is a vector of control variables explained in detail below and in Appendix V. Heteroskedasticity-robust standard errors are clustered by trader.[22]

Table 2.4 reports the results from estimating Equation 2.15 for buy and sell forward transactions and controlling for potential confounding effects. The results without controls can be found in Table A.1 in Appendix VI. The coefficient of interest is *CENT*, which indicates whether forward traders that are more central move the futures market more than other traders.

CENT in the first column shows that, with a one-unit increase in centrality, one would expect the permanent impact of a forward buy transaction on the futures price to rise significantly by 15 bps. Similarly, from the second column, a forward sell transaction by a participant with a one-unit higher centrality impacts the futures price significantly more, by an added -10 bps. The results suggest that the physical oil market contains information that is released via forward trading activity and subsequently incorporated into the futures price. Importantly, central market makers in the forward market seem to be more informed, and therefore their trading activity has a larger price impact. Forward trader identities are visible to other market participants in the OTC trading setup of eWindow. The futures market appears to be alert to the identity of the trader (for example via Platts' PGA service) and reacts more strongly to the actions of traders that are more central. This is in line with the literature on block trades (see for example Holthausen et al., 1987, 1990; Kraus and Stoll, 1972), and particularly the study by

[21] Applying a weighted ECDF, using the number of outgoing edges of a trader, does not materially affect the results.

[22] The results are unchanged if I cluster by date, maturity, and trader.

Chan and Lakonishok (1993), which recognizes trader identity as the dominant driver of price impact. The significant role played by forward market centrality in impacting the futures market price confirms the 'skin in the game' hypothesis.

I control for a variety of potentially confounding effects, without changing the insights obtained from the analysis. The control variables are the log futures volume over the price impact assessment window (*log(VOL)*), the standard deviation of futures log returns over the price impact assessment window (*log(VOLA)*), the forward buy volume in the front-month contract by trading day ($QBUY$), the forward sell volume in the front-month contract by trading day ($QSELL$), the log return between the forward transaction price at time t, and the first quote price of the related order ahead of execution (*log(PM)*), a dummy that takes the value 1 for companies that are oil majors and 0 otherwise ($OILM$), a dummy that takes the value 1 for companies that are commodity trading houses and 0 otherwise ($OILT$), the log Herfindahl-Hirschman Index by forward contract month, where the market share for each trader and contract month is determined by the gross notional of the forwards transacted (*log(HHI)*), a dummy that takes the value 1 after the 1 February 2015 to control for the potential effect of Platts changing the Dated Brent assessment period to 10-30 days ahead ($BMCHG$), a dummy that takes the value 1 after the 1 February 2016 to control for the potential effect of extending the expiry of the futures to two-months-ahead contract and thereby aligning it with the forward contract ($FUTCHG$), and, finally, the dummies accounting for day-of-the-week effects with Monday as the baseline category (*WEEKD()*).

For parsimony, I only discuss the implications for *PE*, the dependent variable of highest interest. On the one hand, *log(VOL)* does not affect the *PE* variable. On the other hand, in the event of a 1% change in *log(VOLA)*, the *PE* of buy and sell transactions is impacted significantly by -0.08% and -0.04% respectively. The $QBUY$ on the day of the executed forward transaction has a statistically, although not economically, significant impact on both the buy and sell *PE*. The *QSELL* only significantly affects the permanent impact of a sell transaction. The price movement in the forward market ahead of the execution of a transaction (*log(PM)*) has a strong impact on the left-hand-side variable. A 1% change in the pre-execution forward price movement of a buy and sell transaction changes the *PE* by 14% and 12% respectively. The affiliation of the forward trader i to big oil (oil majors, *OILM*) or commodity trading (*OILT*) does not impact the coefficient of interest. The *log(HHI)* measuring market concentration and competition has a significant effect on the *PE* of both buy and sell forward transactions. A 1% change in the *log(HHI)* moves the buy and sell *PE* by -0.09% and -0.08% respectively. The dummy variables *BMCHG* and *FUTCHG*, controlling for changes in the forward and futures expiries respectively, do not affect the regression outcome.[23] Finally, day-of-the-week effects (*WEEKD(WED)* for buy and *WEEKD(FRI)* for sell trades) have a significant influence on *PE*. Overall, even after controlling for a variety of possibly interfering effects and events, the conclusions regarding centrality and its price impact remain unchanged.

The adjusted R^2 for the *PE* regressions is 8% for buys and 10% for sells. This is within the range of other studies analyzing the effects of network dynamics on trading variables; for instance, Di Maggio et al. (2017b) report R^2 values between 2% and 8%.

The results for the total price impact in the third and fourth columns align with those for the permanent price impact. A one-unit increase in forward trader centrality leads to a significantly stronger *TE* of forward buy transactions on the futures market, the increase being 20 bps. In the same vein, if a forward trader moves from least to most central, the sell transaction in the forward market impacts the futures market by a significant total of -14 bps. The adjusted R^2 for these regressions ranges from 11% to 14%.

[23] It should be noted, however, that *BMCHG* and *log(VOLA)* have a Pearson correlation of 69% (see Appendix VII), suggesting that futures volatility increased with the changes that were made to the forward contract. *log(VOLA)* might therefore already capture part of this effect. *BMCHG* and *FUTCHG* are also correlated by 56%.

Table 2.4. Price impact of forward trades on futures market: With controls

	Dependent variable:					
	PE		TE		LE	
	Buy	Sell	Buy	Sell	Buy	Sell
CENT	0.15*** (0.05)	−0.10*** (0.04)	0.20*** (0.06)	−0.14*** (0.03)	0.05 (0.04)	−0.04* (0.02)
log(VOL)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	−0.01 (0.01)	−0.01 (0.01)	−0.01** (0.01)
log(VOLA)	−0.08** (0.03)	−0.04** (0.02)	−0.08*** (0.02)	−0.06*** (0.02)	−0.00 (0.02)	−0.01 (0.02)
QBUY	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)	0.00 (0.00)	−0.00 (0.00)	−0.00*** (0.00)
QSELL	−0.00 (0.00)	−0.00*** (0.00)	−0.00** (0.00)	−0.00*** (0.00)	−0.00 (0.00)	0.00 (0.00)
log(PM)	14.26*** (2.04)	11.75*** (1.39)	14.91*** (1.20)	12.31*** (1.34)	0.65 (1.40)	0.56 (0.53)
OILM	−0.00 (0.03)	0.03 (0.02)	−0.03 (0.03)	0.01 (0.02)	−0.03* (0.02)	−0.02 (0.02)
OILT	0.00 (0.03)	0.02 (0.02)	−0.03 (0.03)	0.01 (0.02)	−0.04 (0.02)	−0.01 (0.01)
log(HHI)	−0.09*** (0.02)	−0.08*** (0.02)	−0.03*** (0.01)	−0.02 (0.03)	0.06*** (0.01)	0.05*** (0.02)
BMCHG	0.00 (0.05)	0.00 (0.02)	0.00 (0.03)	0.04* (0.02)	0.00 (0.02)	0.03** (0.02)
FUTCHG	0.05 (0.04)	−0.02 (0.03)	0.05* (0.03)	−0.01 (0.03)	−0.01 (0.03)	0.02 (0.01)
WEEKD(TUE)	0.04 (0.03)	0.01 (0.02)	0.01 (0.02)	0.01 (0.02)	−0.02 (0.02)	0.01 (0.01)
WEEKD(WED)	−0.06*** (0.02)	0.00 (0.02)	−0.04*** (0.01)	−0.01 (0.02)	0.02 (0.01)	−0.01 (0.02)
WEEKD(THU)	−0.02 (0.03)	−0.01 (0.02)	−0.03 (0.02)	−0.00 (0.02)	−0.00 (0.02)	0.00 (0.01)
WEEKD(FRI)	−0.02 (0.03)	−0.05** (0.02)	−0.01 (0.02)	−0.00 (0.02)	0.02 (0.02)	0.04** (0.02)
Constant	−1.15*** (0.36)	−0.44** (0.20)	−1.03*** (0.23)	−0.33 (0.23)	0.13 (0.20)	0.11 (0.15)
Observations	2,083	2,473	2,083	2,473	2,083	2,473
R^2	0.09	0.10	0.15	0.12	0.03	0.04
Adjusted R^2	0.08	0.10	0.14	0.11	0.02	0.04
Residual Std. Error	0.27 (df = 2067)	0.26 (df = 2457)	0.21 (df = 2067)	0.22 (df = 2457)	0.18 (df = 2067)	0.17 (df = 2457)

Notes: *p<0.1; **p<0.05; ***p<0.01. *CENT* measures the centrality of the forward market participants in terms of the ECDF-normalized weighted out-degree [0 = least central; 1 = most central]. Please refer to Appendix V for a detailed explanation of the control variables. The coefficients are reported in percentage terms (%). Robust standard errors clustered at the trader level are reported in parentheses.

Lastly, the liquidity effect, shown in the fifth column of Table 2.4, of a forward buy transaction on the futures price is insignificant. For the liquidity effect in the sixth column, I find that a one-unit rise in centrality leads to a significant reversal at the 10% level in the futures price—the *LE* of a forward sell transaction amounts to -4 bps. The adjusted R^2 here lies between 2% and 4%.

All in all, the findings support the 'skin in the game' hypothesis. Trading activity by central forward participants seems to convey valuable information to the financial market that is subsequently impounded into futures prices.

D. Robustness tests

In this section, I corroborate that it is indeed the centrality in the forward trading network that matters. As described in Section II, other products are traded in the physical market during the Platts Window. The OTC-traded CFD market is the most liquid of those, while the cargo market is the least liquid, as measured by the number of trades and quotes. While the CFD and cash BFOE markets are closely interlinked, the participant groups of both markets are similar but different at the same time. For example, some participants who are very active in the forward market occupy a less prominent role in the CFD market and vice versa, and again others are crucial participants in both. Additionally, some engaged CFD traders decide not to participate in the forward market at all. At the same time, all forward traders participate in the CFD market. Hence, I compute the centrality of all traders in the CFD market and substitute the forward trader centrality used in the previous section with the CFD centrality, to determine the importance of the traders anew. CFD trading allows market participants to minimize the risk arising from price differentials between elements of the Brent complex, and therefore forward traders with high CFD centrality scores might be well informed about oil fundamentals too.

Table 2.5 shows that the CFD *CENT* coefficient is insignificant in explaining the *PE*, *TE*, and *LE* of forward transactions on the futures price.[24] This finding supports the assertion that the forward network centrality is a valuable proxy for 'skin in the game' information from upstream and downstream business lines. The fact that cash BFOE contracts are used to trade long-term supply and demand, while CFDs serve to manage short-term exposures and to hedge price risks of the Brent complex, might help to explain the difference in importance. In addition, forward trading requires the ability to receive and deliver physical oil, while CFDs are cash settled derivatives (see Barret, 2012a). The business of forward participants thus demands higher infrastructure investments and closer integration with the upstream and downstream petroleum industry. Given the closeness of forwards and futures, the link is stronger and the information is more easily observed and impounded. Therefore, forward network centrality is a valid proxy for supply and demand fundamentals in the physical oil market that are revealed via trading and subsequently incorporated into futures prices.

[24] I also test the importance of the forward and CFD centrality measures in jointly explaining the price impact in the futures market. While the forward centrality is highly significant, the CFD centrality does not affect the price impact variables.

Table 2.5. Price impact of forward trades: CFD market centrality

	Dependent variable:					
	PE		TE		LE	
	Buy	Sell	Buy	Sell	Buy	Sell
CENT	0.07 (0.05)	−0.02 (0.03)	0.10 (0.07)	−0.03 (0.05)	0.03 (0.04)	−0.01 (0.04)
log(VOL)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	−0.01 (0.01)	−0.01 (0.01)	−0.01** (0.01)
log(VOLA)	−0.08** (0.03)	−0.05** (0.02)	−0.08*** (0.02)	−0.06*** (0.02)	−0.00 (0.02)	−0.02 (0.02)
QBUY	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)	0.00 (0.00)	−0.00 (0.00)	−0.00*** (0.00)
QSELL	−0.00 (0.00)	−0.00*** (0.00)	−0.00** (0.00)	−0.00*** (0.00)	−0.00 (0.00)	0.00 (0.00)
log(PM)	14.29*** (2.08)	11.67*** (1.38)	14.95*** (1.33)	12.22*** (1.29)	0.66 (1.40)	0.55 (0.54)
OILM	0.04 (0.03)	0.00 (0.02)	0.01 (0.03)	−0.03 (0.02)	−0.02 (0.02)	−0.03* (0.02)
OILT	0.03 (0.02)	−0.00 (0.02)	0.01 (0.03)	−0.02 (0.02)	−0.03 (0.02)	−0.01 (0.02)
log(HHI)	−0.09*** (0.02)	−0.08*** (0.02)	−0.02** (0.01)	−0.03 (0.03)	0.06*** (0.01)	0.05*** (0.02)
BMCHG	−0.00 (0.05)	0.01 (0.03)	−0.00 (0.03)	0.04* (0.02)	0.00 (0.02)	0.04** (0.02)
FUTCHG	0.05 (0.04)	−0.02 (0.03)	0.04 (0.03)	0.00 (0.03)	−0.01 (0.03)	0.02 (0.01)
WEEKD(TUE)	0.04 (0.03)	0.01 (0.02)	0.01 (0.02)	0.02 (0.02)	−0.02 (0.02)	0.01 (0.01)
WEEKD(WED)	−0.06*** (0.02)	0.01 (0.02)	−0.04*** (0.01)	−0.01 (0.02)	0.02 (0.01)	−0.01 (0.02)
WEEKD(THU)	−0.02 (0.03)	−0.01 (0.02)	−0.03 (0.02)	−0.00 (0.02)	−0.00 (0.02)	0.00 (0.01)
WEEKD(FRI)	−0.02 (0.03)	−0.04*** (0.02)	−0.00 (0.02)	−0.00 (0.02)	0.02 (0.02)	0.04** (0.02)
Constant	−1.10*** (0.37)	−0.51** (0.20)	−0.97*** (0.23)	−0.42** (0.21)	0.13 (0.18)	0.09 (0.16)
Observations	2,083	2,473	2,083	2,473	2,083	2,473
R^2	0.09	0.10	0.13	0.11	0.03	0.04
Adjusted R^2	0.08	0.09	0.13	0.10	0.02	0.04
Residual Std. Error	0.27 (df = 2067)	0.26 (df = 2457)	0.21 (df = 2067)	0.23 (df = 2457)	0.18 (df = 2067)	0.17 (df = 2457)

Notes: *p<0.1; **p<0.05; ***p<0.01. *CENT* measures the physical CFD market trader centrality in terms of ECDF-normalized weighted out-degree [0 = least central; 1 = most central]. Please refer to Appendix V for a detailed explanation of the control variables. The coefficients are reported in percentage terms (%). Robust standard errors clustered at the trader level are reported in parentheses.

V. Conclusion

Despite the fact that the financial and physical oil markets are, and have historically been, inextricably linked, our understanding of the futures market has gradually increased while we still know very little about its physical counterpart—the forward market.

I create a unique and novel dataset by combining intraday data for both markets. I confirm the longstanding belief that the futures market is nowadays the dominant information leader, incorporating the majority of new information ahead of the forward market. This finding is unsurprising given that the virtually 24-hour exchange-traded and financially settled futures contracts are by design more active. However, the forward market, with its proportionally few quotes and transactions and only a selected number of active participants, is contributing a non-trivial amount to oil price discovery. During only five minutes of active trading, from 16:25 to 16:30, at the end of the day, forwards impound approximately 20% of the innovations to the efficient price of oil. The forward price is also less noisy than the futures price. This is in line with the findings of Chapter 1, suggesting that physical market activity during the time of the Dated Brent benchmark assessment does indeed substantially influence the futures price development.

Lastly, I show that information from the physical market is revealed via forward trading and subsequently incorporated into futures prices. In support of my hypothesis, I find that more central forward participants with substantial 'skin in the game' have a more pronounced futures price impact. A one-unit increase in forward network centrality corresponds to a 10 bps to 15 bps stronger permanent price impact. The informational advantage of central traders likely stems from proprietary business insights gleaned from their oil supply chains, for example through infrastructure stakes, such as oil field or refinery ownership, and trading relationships with other major players in the market. The results suggest that fundamental supply and demand information is a significant driver of commodity prices.

The findings need to be interpreted in the light of a few limitations. First, forward trading is limited to a very short period every day. I do not wish to make any inferences about oil price discovery outside of this window. Future research should aim to reconcile data on ET derivatives with that on other OTC derivatives and investigate their interactions. CFDs, for example, play a crucial role in the physical oil market too. Second, the data limitations that cause difficulties in the establishment of cointegration between oil futures and forwards on an intraday basis show there is a call for caution when interpreting the price discovery findings. While the results are conservative, the price discovery metrics depend, by design, on the specifications of the VECM.

Despite these constraints, I confirm assertions in the literature that the financialization of commodity markets substantially affects the way oil is traded (see Cheng and Xiong, 2014). However, I underline that there is a close interaction between financial and physical contracts, with unique features of both markets contributing to the determination of the efficient oil price.

3

The visible hand: Benchmarks, regulation, and liquidity

Abstract

The model in this study shows that a more precise benchmark assessment can improve welfare by overcoming traders' and regulators' inabilities to penalize dealers sufficiently.[1] I exploit a benchmark regime change in the $289 trillion interest rate swaps market to test the model predictions. Utilizing proprietary order book data on electronically traded swaps, I find robust improved quality effects in the underlying market following the regime change. Regulations that increase the assessment precision can, therefore, have positive effects on the overall market. Conservative estimates of direct savings in a single swap tenor on one trading platform are in the region of $4m-$7m.

JEL classification: G14, G18, G24.

Keywords: benchmarks, regulation, interest rates, ISDAFIX, ICE Swap Rate

[1] I acknowledge that the theoretical model in Section II of this chapter is the intellectual work of Andrea Pirrone and originates from a collaboration during my time as a visiting researcher at the Financial Conduct Authority (FCA) in London.

I. Introduction

Benchmarks are critical to the efficient functioning of markets. Many industries, but particularly the financial services industry, use benchmarks to settle contracts, monitor trade execution, and signal sentiment in the market. They also serve as reference rates for fund managers and increase price transparency for investors. However, information asymmetries, market power, and design inefficiencies may prevent markets from working well (Iscenko et al., 2016). Until very recently, benchmarks were not subject to any regulatory supervision. This changed in 2013, after well-publicized scandals about the alleged manipulation of LIBOR, the WM/Reuters FX benchmark, the LBMA Gold Price, and the ISDAFIX rate, prompting the Financial Conduct Authority (FCA) to start regulating a total of eight benchmarks.[2]

Duffie et al. (2017) show that the introduction of a benchmark improves the trade matching process in opaque over-the-counter (OTC) markets and can enhance social welfare as it improves the information available to traders and reduces their search costs leading to increased price transparency.[3] For this reason, a benchmark encourages dealers to compete aggressively for the best price, prompts more efficient dealer-trader matching, and increases the volume of beneficial transactions. Increased inter-dealer competition improves market liquidity and reduces transaction costs. Specifically, "the most efficient dealers can use a benchmark as a 'price transparency weapon' that drives inefficient competitors out of the market" (Duffie et al., 2017, p. 3). However, when discussing welfare effects, Duffie et al. (2017) only contrast a market with a benchmark to a market without a benchmark. This approach offers no opportunity for a theoretical examination of the economic effects of an increase in the 'quality' of a hitherto unregu-

[2] The benchmarks are LIBOR, SONIA, RONIA, WM/Reuters 4 pm London Closing Spot Rate, ICE Swap Rate, LBMA Gold Price, LBMA Silver Price, ICE Brent Index (see `https://www.fca.org.uk/markets/benchmarks/powers`).

[3] A vast literature exists on search costs, such as pecuniary and time costs (see for example Duffie, 2012; Duffie et al., 2005; Duffie and Zhu, 2017; Flood et al., 1999; Zhu, 2012).

lated benchmark, which would be helpful given that improvements in quality are a likely result of the regulations mentioned above. This paper fills this gap by showing that appropriate regulatory intervention encourages an increase in the precision of the benchmark fixing process and thus induces a reduction in pricing noise. As a consequence, the quality of the underlying market improves too.

In the spirit of Stiglitz (1993), who questions the government's role in financial markets, the model predicts that regulating a benchmark can be positive for the market, and provides a solid theoretical rationale for many of the recent interventions made by policy makers in this area.

In the model, traders cannot observe dealers' marginal costs but, as in Duffie et al. (2017), they can observe a public signal (i.e., the benchmark), which aggregates the information, but with noise. The noise represents traders' different interpretations of the same signal (because of a lack of precision in the benchmark fixing) and imperfections in the benchmark assessment between the dealers themselves (because of a lack of quality in the production cost data). Due to the information asymmetry between dealers and traders, traders have to pay more than the efficient cost, and this impairs welfare. To solve this problem, traders and regulators can decide to 'punish' dealers if the benchmark realization shows they are taking advantage of their position by charging an excessive price. However, penalties are limited: traders can only decide not to buy from the dealers, and the regulatory fines necessary to restore the optimal allocation may be too high to be practically implemented. The constraints preclude the implementation of the optimal outcome, which would be for traders to pay a price close to the cost of production. Having said that, a policy that reduced the noise in the benchmark fixing process by increasing precision would overcome these limitations and restore the optimal outcome.

I test the theoretical prediction of the model that a well-designed benchmark regime change (BRC) will have positive effects on the liquidity of the underlying market, using a natural experiment generated by the FCA in 2015. Specifically, I exploit the 31 March 2015 transition from the unregulated panel-based ISDAFIX benchmark to the regulated market-based ICE Swap Rate—a fundamental transformation of the benchmark, which is central to the \$289 trillion swaps market and used, for example, in hedging interest rate risk. The BRC, induced by the FCA, introduced controls and regulatory oversight, as well as a new assessment methodology—the transparency effects of which should be analogous to the modeled reduction of noise in the benchmark assessment. I find that the BRC has a positive effect on the representativeness and accuracy of the benchmark rate, measured as the differential between the proxied execution price of a standard market size (SMS) trade on-platform and the benchmark rate. At the end of the assessment, and at the time of publication, the benchmark rates under the new regime are between 22% and 68% closer to market prices.

Furthermore, I study proprietary order book data and show that market liquidity improves following the BRC, as measured by quoted spreads, depth, and execution costs. Spreads narrow significantly, by 14%. Despite the fact that quoted depth at the best bid and offer decreases, the overall 10-level order book depth increases slightly, and executions of SMS orders become cheaper. As an aggregate measure of the combined effects on spreads and depth, the proxied roundtrip costs of completing a buy transaction and a sell transaction also decrease by roughly 11% following the BRC. Difference-in-difference regressions further show that the significant increase in liquidity is more pronounced for benchmark-grade swaps, i.e., swaps for which a regulated benchmark rate is assessed daily, than for non-benchmark-grade swaps following the transition to the new benchmark regime. The findings demonstrate that the BRC has a positive effect on the liquidity of benchmark-grade swaps over and above other influences, such as increases in venue participation by so-called 'streamers'[4]. I therefore directly link the improvement in on-platform execution costs to the regulatory intervention of the FCA. Well-designed policy interventions can indeed be beneficial for the functioning of financial markets (see for example Barth et al., 2013; Stiglitz, 1993). The results are robust to controlling for a multitude of confounding effects such as volatility and macroeconomic events and alternative regression specifications. Moreover, I endogenously test for structural breaks in the time series of the liquidity measures employed and identify significant breaks in alignment with the BRC.

The paper adds to the research stream on financial benchmarks and their interactions with the underlying markets. Existing research focuses on the trading patterns of financial products around the assessment periods of short-term loans, precious metals, oil, and foreign exchange benchmarks. Abrantes-Metz et al. (2012) study the market dynamics around the setting of the benchmark for short-term interest rates, and find patterns suggestive of anticompetitive behavior in the 1-month LIBOR rate. Monticini and Thornton (2013) analyze the conjecture that some panel participants have understated their LIBOR submissions and present evidence that this behavior has likely led to a reduction in the reported rate. Meanwhile, Fouquau and Spieser (2015) apply a novel technique that allows them to detect possible cartels. Their findings are underscored by the regulators' fining of banks for their involvement in the 2012 LIBOR manipulation scandal. Recent examinations of commodities markets have also indicated patterns of exploitation of benchmark processes. Caminschi and Heaney (2014) deduce that information leaks from the physical London PM Gold price fixing into the gold derivatives market ahead of the official price publication. In Chapter 1, I report similar evidence of a consistent price trend in the Brent futures in the direction of the benchmark outcome during the Platts Dated Brent assessment. Finally, the papers by Osler and Turnbull

[4]Streamers are most often dealer banks that continuously 'stream' firm quotes to trade interest rate products on regulated electronic trading venues.

(2017) and Evans (2018) focus on foreign exchange and the WM/Reuters London 4 pm FX fix. While the former models dealer behavior around benchmark price assessments and derives trading patterns that suggest collusion among participating dealers, the latter finds currency price movements that align with collusive activities.

The literature stream on benchmark manipulation and price patterns around the times of assessments has led to a set of theoretical papers focusing on the design and reform of financial benchmarks and the benchmarks' value for financial markets (Coulter et al., 2018; Duffie and Dworczak, 2018; Duffie et al., 2017; Duffie and Stein, 2015; Eisl et al., 2017; Perkins and Mortby, 2015).[5] For instance, in addition to Duffie et al. (2017), who describe the importance of benchmarks for financial markets, Duffie and Stein (2015) argue that robust benchmarks should be based on concluded transactions and not market participants' subjective judgments. The reformed ICE Swap Rate that is the focus of my analysis takes a step in the right direction, being computed from tradable and transparent electronic quotes. The authors also acknowledge the vital role of regulators in supporting effective transitions to better benchmarks. Furthermore, Duffie and Dworczak (2018) study the computation of transaction-based reference rates and make suggestions on the optimal design. Coulter et al. (2018) and Eisl et al. (2017) investigate different assessment procedures and make specific recommendations for the reform of LIBOR.

With this study, I make three key contributions to the growing literature on benchmarks. Firstly, I propose a model that theoretically motivates recent regulatory benchmark interventions and the expected improvements to both benchmarks and markets. Secondly, I test the model predictions and those of Duffie et al. (2017) within an empirical framework and provide evidence concerning the effects of transparent and regulated

[5] A related strand of the literature analyzes changes to transparency and competition, often induced by changes to market infrastructure and regulation (see for example Benos et al., 2016; Bessembinder et al., 2006, 2013; Boehmer et al., 2005; Edwards et al., 2007; Goldstein et al., 2007; Harris and Piwowar, 2006; Trebbi and Xiao, 2017).

benchmarks on market quality. The proprietary full order book dataset, covering roughly 50% of the electronic inter-dealer interest rate swaps (IRS) market, allows me to directly analyze and document the microstructure of the world's largest derivatives market for the first time in the academic literature. Thirdly, I add to the debate on the impact of regulatory interventions on the efficient functioning of financial markets.

The remainder of this paper is organized as follows: the next section (II) presents the model and Section III describes the institutional background, introduces the data, and provides descriptive statistics on the electronic trading of swaps. Section IV details the main results, while additional robustness tests can be found in Section V. Section VI concludes.

II. The model

This section presents a simple model to explain how regulations and changes of methodologies may affect markets by improving the accuracy of benchmarks. In the model, information asymmetries allow dealers to extract an information rent from the traders. When the accuracy of the benchmark improves, the rent decreases and markets tend to conform to the optimal allocation.

A. Structure of the model

The model starts with a market of risk-neutral dealers and traders. As in Duffie et al. (2017), n dealers sell a homogeneous good to a continuum of traders who differ in their search costs. The timing of the game is as follows: (i) nature draws dealers' marginal costs, traders' search costs, and the benchmark realization; (ii) dealers move first and set the price of the good; (iii) traders observe the prices in the market and the benchmark realization, and decide whether to enter the market.

B. The benchmark

A trader either buys one unit of the good and pays the price p_i to dealer i, or stays outside the market. Each dealer supplies the same good from the wholesale market and has a cost of production a_i for each unit. Production costs, which are also marginal costs, are heterogeneous and measure dealers' efficiencies. A dealer with a low a is more efficient than a dealer with a high a; each dealer only knows its own marginal cost.

Traders cannot observe dealers' marginal costs, but they use the benchmark y to observe (with noise) the average cost of production in the dealer market. The benchmark y is, therefore, defined as

$$y = \sum_{i=1}^{n} \frac{a_i}{n} + \epsilon \tag{3.1}$$

where $\epsilon \sim F(0, \sigma^2)$ is the noise component, with density f and cumulative distribution F. As $\sigma \to 0$, the benchmark becomes more precise, so the noise represents the accuracy of the benchmark fixing.

C. Quantities sold by the different dealers

The n dealers sell a homogeneous good and post prices ordered from the lowest to the highest:

$$p_1 \leq p_2 \leq \cdots \leq p_n$$

The assumption is that traders expect to find any of the prices with equal probabilities:[6]

$$Pr(p_1) = \cdots = Pr(p_n) = 1/n$$

The price distribution is common knowledge among the traders, but the traders do not know whether the price charged by the next dealer will be higher or lower if they continue

[6]This assumption leads to closed-form solutions for the demand curves but can be relaxed as in Duffie et al. (2017).

searching. For tractability, a trader can always go back to a previous dealer.

Traders have heterogeneous search costs. $G(x)$ represents the share of traders with costs lower than x and has the following uniform distribution:

$$G(x) = \begin{cases} \frac{x}{s} & \text{if } 0 \leq x \leq v - p^* \\ \frac{v-p^*}{s} & \text{if } x > v - p^* \end{cases} \tag{3.2}$$

where v is the value attached to the good by every trader, $p^* \equiv \sum_j p_j/n$ is the average price, and s is the density for $0 \leq x \leq v - p^*$.[7]

In equilibrium, each trader j stops searching and pays p_i when the expected gain from searching for a price lower than p_i equals j's search costs. The equilibrium condition is therefore

$$x_j = \sum_{k=1}^{i-1} (p_i - p_k) Pr(p_k) \tag{3.3}$$

where x_j represents j's search costs and $\sum_{k=1}^{i-1}(p_i - p_k)Pr(p_k)$ is the expected gain from searching for a price p_k lower than p_i.

Let q_i be the quantity demanded of a dealer with price p_i. A dealer with price p_i sells to two groups of traders: (i) traders who randomly found p_i, despite being willing to pay a price $p_{i+1} > p_i$ (the demand of dealers with prices higher than p_i); (ii) traders with search costs higher than the expected gain from searching for a price lower than p_i. Both types of traders are represented formally in the equation below:

$$q_i = q_{i+1} + \frac{1}{i}\left[G(x_{i+1}) - G(x_i)\right]$$

Using the equilibrium condition (3.3), the expected demand for the dealer with price

[7] The distribution is scaled by the average price p^* to simplify the algebra. The case without scaling is given in the appendix.

p_i simplifies to (see Carlson and McAfee, 1983)

$$q_i = \frac{v - p_i}{sn} \tag{3.4}$$

As expected, the demand for dealer i depends positively on traders' valuation of the good (v), and negatively on the price dealer i charges (p_i). The demand for a single dealer is also affected by the traders' density and the number of dealers in the market (sn).

D. Prices

Traders can exit the market if they infer that dealers are overcharging them by observing a realization of the benchmark lower than a certain threshold.[8] If traders leave the market, demand drops and dealers need to charge a lower price. This behavior is modeled using the penalty parameter Δ.[9] The next section models what happens as the threshold $\bar{y}$ changes, but for the time being the focus is on the dealers' profits.

The profits of dealer i are

$$\pi_i \equiv \left[F\left(\bar{y} - \frac{\sum_i a_i}{n}\right)(p_i - \Delta) + \left(1 - F\left(\bar{y} - \frac{\sum_i a_i}{n}\right)\right) p_i - a_i \right] q_i \tag{3.5}$$

where p_i is the price offered by dealer i; $F\left(\bar{y} - \frac{\sum_i a_i}{n}\right)$ is the probability that the realization of the benchmark is below the threshold $\bar{y}$; Δ is the penalty when the signal realization is below the threshold.

[8] One can assume that traders have an incentive to penalize the dealers by exiting the market because this behavior would lead to a lower expected price. In the appendix, it is shown that this is equivalent to assuming that traders particularly value the asset.

[9] The penalty parameter describes, in a reduced form, the behavior of a repeated game in which a trader would cease any activity with the dealer if the realization of the signal were below the threshold, i.e., if he could infer that the dealer was overcharging him. For an analogous structure, see Ritter and Taylor (2010).

Competition among dealers drives their profits to zero. From (3.5) it follows that

$$p_i = a_i + \Delta F \left(\bar{y} - \frac{\sum_i a_i}{n} \right) \tag{3.6}$$

and from (3.4),

$$q_i = [v - a_i] / sn - \frac{\Delta F \left(\bar{y} - \frac{\sum_i a_i}{n} \right)}{sn}$$

which clarifies that the traders punish the dealers by exiting the market when they infer that the marginal costs are below the threshold, i.e., when dealers overcharge them.

Each dealer i sets the price p_i to minimize the penalty Δ, yielding

$$\Delta = \frac{n}{f \left(\bar{y} - \frac{\sum_i a_i}{n} \right)}$$

(the proof is in the appendix). Substituting this back into (3.6) gives

$$p_i = a_i + n \frac{F \left(\bar{y} - \frac{\sum_i a_i}{n} \right)}{f \left(\bar{y} - \frac{\sum_i a_i}{n} \right)} \tag{3.7}$$

Therefore, the dealers add a mark-up on top of the cost of production to determine the price at which they are wiling to sell. In the moral hazard literature, this mark-up is known as 'information rent' as it relies on the dealers' informational advantage.

E. Threshold and precision

The traders' behavior as the threshold $\bar{y}$ changes can now be analyzed (as in Holmstrom, 1982). It is assumed that F is normally distributed. Then, from (3.7), as traders decrease the threshold at which they would leave the market (i.e., $\bar{y} \to -\infty$), the penalty for dealers increases ($\Delta \to +\infty$), and $F \left(\bar{y} - \frac{\sum_i a_i}{n} \right) / f \left(\bar{y} - \frac{\sum_i a_i}{n} \right) \to 0$, implying that traders achieve their first best $p_i = a_i$ in which dealers do not charge a mark-up at all.

However, traders cannot achieve $\bar{y} \to -\infty$ as production costs cannot be negative. Moreover, an external authority, such as a market regulator, cannot achieve $\Delta \to +\infty$, as this level of regulatory fine is simply impossible.

On the other hand, a regulator can improve the outcome by reducing the noise in the benchmark fixing. Suppose that traders choose the optimal threshold level $\bar{y}$, after observing the price p_i. Traders maximize their utility,

$$\max_{\bar{y}} v - p_i(a_i, \bar{y})$$

from which the following equation is obtained (the derivation is in the appendix), describing the price set by each dealer i:

$$p_i = a_i + n\sigma \frac{h(\zeta)}{h'(\zeta)} \tag{3.8}$$

where $\zeta \equiv \frac{\bar{y} - \frac{\sum_i a_i}{n}}{\sigma}$, and $h(\zeta)$ is ζ's density function. Using this equation in (3.4), the expected demands in equilibrium are also obtained:

$$q_i = \frac{v - a_i - n\sigma \frac{h(\zeta)}{h'(\zeta)}}{sn} \tag{3.9}$$

Equation (3.8) is crucial to understand the expected effects of the BRC on the market. An increase in precision reduces the noise in the benchmark fixing (σ) and moves the outcome closer to the first best by reducing noise in the prices (Equation 3.8), and increasing participation in the market (Equation 3.9). If the noise in the benchmark assessment process is eliminated, i.e., $\sigma = 0$, then the first best can be achieved irrespectively of the level of penalties. In this case, the price that traders pay matches the exact cost of production of each dealer.

The model simplifies many aspects of the analysis to obtain simple closed-form solutions. However, it represents, in a stylized way, the critical elements of a market in which traders use the benchmark to monitor dealer activity. I anticipate the BRC to have an analogous effect to a reduction of σ, because the new methodology and the FCA regulation introduced systems and controls that have made the benchmark fixing process more transparent and reduce the possibility of manipulation. Therefore, I expect a reduction of noise in fixed-for-floating IRS prices and an increase in market liquidity due to increased participation.

III. Institutional details and data summary

A. The swap market

Fixed-for-floating IRS (henceforth also simply referred to as swaps) are predominately traded on regulated trading venues, where buyers and sellers meet to exchange cash flows based on a notional amount, with one party paying the fixed rate and receiving the floating rate and vice versa. Each payment series of a swap is defined as a fixed or floating leg. Given the prominence of USD IRS, with a notional amount outstanding of $139 trillion,[10] my focus lies on the USD segment only. The data used for the USD ICE Swap Rate benchmark assessment, which determines the fixed leg price, are sourced from the order books of participating swap execution facilities (SEFs).[11] SEFs were introduced by the Dodd-Frank Wall Street Reform and Consumer Protection Act (the so-called Dodd-Frank Act), which stipulates the mandatory trading of certain traditional OTC

[10]See the statistics produced by the Bank for International Settlements (BIS) (`http://stats.bis.org/statx/srs/table/d5.1`) for more details.

[11]The four electronic trading venues are Trad-X (Tradition), BGC Trader (BGC Partners), i-Swap (ICAP), and tpSWAPDEAL (Tullett Prebon, nowadays merged with ICAP), which are authorized multilateral trading facilities (MTFs) in the UK and also operate SEFs under US legislation. For the EUR and GBP benchmark assessments, the data are sourced from the MTF order books. For the USD benchmark assessment, data are sourced from the respective SEF order books.

derivatives, such as swaps, on regulated venues to promote competition and enhance transparency. As such, SEFs are electronic trading platforms that post and execute bids and offers to trade swaps from multiple participants. Under the mandatory trade execution requirement, swaps made available to trade (MAT)[12] are required to be traded on SEFs over the full length of the sample period. A list of the USD IRS maturities captured by the MAT mandate can be found in Table 3.1. A benchmark rate is assessed for all tenors covered by the MAT requirement, except for the 12Y swap—a peculiarity that I use to my advantage in the difference-in-difference analysis in this study.

Table 3.1. Fixed-for-floating interest rate swaps

	Currency	Maturity
MAT	USD	1Y, 2Y, 3Y, 4Y, 5Y, 6Y, 7Y, 10Y, **12Y**, 15Y, 20Y, 30Y
ICE Swap Rate assessment	USD	1Y, 2Y, 3Y, 4Y, 5Y, 6Y, 7Y, 8Y, 9Y, 10Y, 15Y, 20Y, 30Y

Notes: This table shows the tenors, which are captured by the MAT mandate, and those for which IBA is assessing the ICE Swap Rate benchmark. The USD MAT swaps relevant for this study have a 3-month LIBOR interest rate basis, a semi-annual payment frequency, and a day count convention of 30/360, aligning with the characteristics of swaps feeding into the assessment by IBA. The MAT mandate for USD tenors was implemented in February 2014. Under the ICE Swap Rate regime, no benchmark rate is assessed for the 12Y USD tenor, which is relevant for later parts of this study. See http://www.cftc.gov/idc/groups/public/@otherif/documents/file/swapsmadeavailablechart.pdf and https://www.theice.com/iba/ice-swap-rate for more information.

Rules further require that registered SEFs must, as a minimum, operate limit order books (LOB) for all listed swaps. The platforms can also offer request for quote (RFQ) or voice-based functionalities in conjunction with the LOB, and therefore often run a hybrid model, pairing electronic and voice broking.

[12]MAT is a procedure used to determine whether a swap that is required to be cleared is subject to the trade execution requirement and must be traded on a SEF from the effective date of February 2014 onwards, using one of the minimum execution methods. As such, a SEF establishes whether a swap is MAT based on predefined criteria such as availability of buyers and sellers, and trading frequency and volume, and submits the determination to the Commodity Futures Trading Commission (CFTC) for approval. Once certified by the CFTC, the MAT swap needs to be traded per the trade execution requirement on all SEFs.

B. The regulation of benchmarks

Given the economic significance of the IRS market and its high degree of interconnectedness with the fixed income and money markets, the need for a reference price in the form of a standardized benchmark rate for valuing and settling contracts was recognized early on. The ICE Swap Rate, formerly known as the ISDAFIX rate, is used in the valuation of, for example, early-terminated IRS, cash settled swaptions, interest rate indexes, and many others.

The International Swaps and Derivatives Association (ISDA) established the leading benchmark for fixed rates on swaps in 1998. The benchmark rates were assessed based on submissions made by a panel of 16 banks representing the mid-market rates at which they were willing to trade an SMS swap in the current market environment. The SMS differs across tenors and is $50m for the 10-year (10Y) USD contract, which is the most liquid and actively traded tenor in the sample. For USD swaps, the panel submission polling window ran from 11:00:00 to 11:15:00 ET and the ISDAFIX rates were published at 11:30:00 ET (see Panel A of Figure 3.1).[13] In order to establish the daily benchmark rates, a trimmed mean of the submitted rates was computed, which depended on the number of bank participants.

On 1 August 2014, the ICE Benchmark Administration (IBA) took over full responsibility from ISDA for the USD, EUR, and GBP assessments. IBA maintained the old submission-based methodology until 30 March 2015 (inclusive). The change of benchmark administrators was part of a wider attempt to enhance the integrity and robustness of benchmarks after investigations by regulators around the world into claims of misconduct and manipulation of them.[14]

[13] See https://web.archive.org/web/20140706105057/http://www2.isda.org/attachment/NjQ1OA==/ISDAFIX%20USD%20Rates%2016%20April%202014.pdf.

[14] The FCA issued fines amounting to a total of over £2 billion: https://www.fca.org.uk/markets/benchmarks/enforcement. In the US, the CFTC settled multiple charges for attempted manipulation of the ISDAFIX rate. See for example http:

On 31 March 2015 IBA transitioned from the submission-based assessment system to an automated and market-based methodology, thus, for the first time assessing the benchmark rates by relying on *tradable* quotes from regulated electronic trading venues. The benchmark was renamed the ICE Swap Rate, taking effect from 1 April 2015.[15] The methodological change went hand-in-hand with the introduction of regulatory supervision by the FCA also starting 1 April 2015. A timeline of events is illustrated in Panel B of Figure 3.1.

The ICE Swap Rate is the principal global benchmark setting the fixed leg price for IRS at a particular time of day, and is assessed for tenors ranging from 1 to 30 years. By means of example, the USD ICE Swap Rate, assessed during the morning run, represents the mid-price for the execution of an SMS [16] trade. The rate is based on the best available prices across trading venues, collected from 10:58:00 to 11:00:00 ET, and is published at 11:15:00 ET (see Panel C of Figure 3.1).

The two-minute data collection window is divided into 24 blocks of five seconds, and a random snapshot is taken from the order book of each trading venue during each of the blocks. At each snapshot time, the benchmark administrator creates a synthetic order book from the snapshots collected from all venues by ranking the quotes by price. The order book is then used to calculate the volume-weighted bid, offer, and average mid-price to execute an SMS order. This process is repeated for each snapshot time, and after discarding illiquid and outlier snapshots, the remaining snapshots are quality-weighted[17]

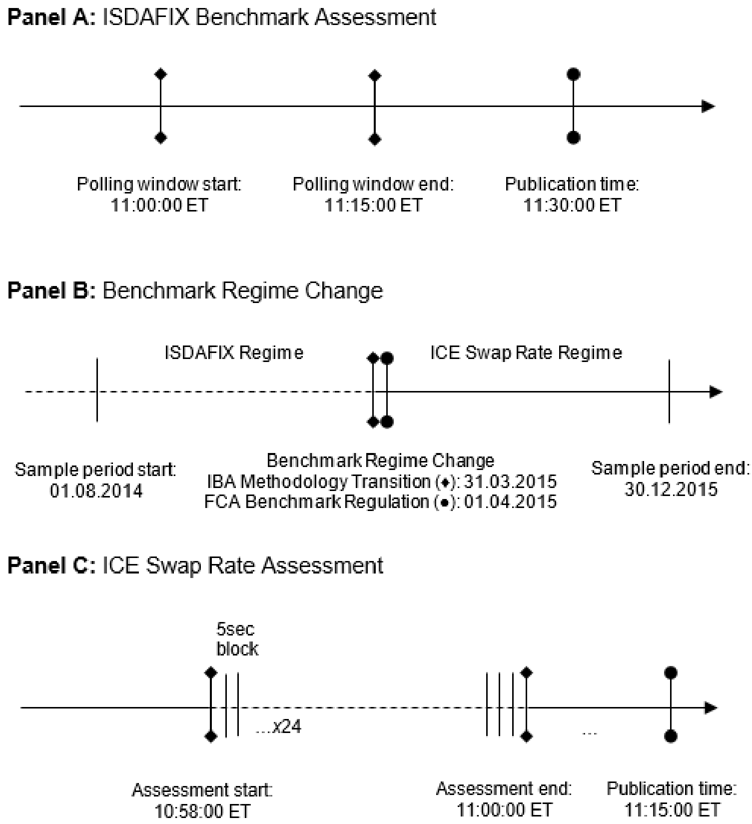
//www.cftc.gov/PressRoom/PressReleases/pr7505-16, http://www.cftc.gov/PressRoom/PressReleases/pr7527-17, and http://www.cftc.gov/PressRoom/PressReleases/pr7371-16.

[15]See http://ir.theice.com/press/press-releases/all-categories/2015/04-01-2015 for the official press release.

[16]The SMS differs by currency and tenor as set out by IBA in their methodology document: https://www.theice.com/publicdocs/ICE_Swap_Rate_Full_Calculation_Methodology.pdf.

[17]The quality weight is determined based on the tightness of the spread between the volume-weighted bid and volume-weighted offer. The full methodology can be found here: https://www.theice.com/publicdocs/ICE_Swap_Rate_Full_Calculation_Methodology.pdf.

Figure 3.1. Timeline of events



Notes: Panel A shows the polling and publication times under the old ISDAFIX regime. Panel B shows the timeline of events of the BRC. The sample period starts on the 1 August 2014 and ends on 30 December 2015. On 31 March 2015 (♦) ICE Benchmark Administration successfully transitioned to the new assessment methodology. The FCA regulatory regime for the ICE Swap Rate started on 1 April 2015 (●). Panel C shows the assessment and publication times under the new ICE Swap Rate regime.

to calculate the ICE Swap Rate.

C. Order book data and descriptive statistics

For the USD ICE Swap Rate assessments, IBA collects data from three trading venues, namely Trad-X (Tradition), BGC Trader (BGC Partners) and i-Swap (ICAP).[18] I obtain the full proprietary order book data of the Trad-X SEF for swaps cleared by the London

[18]Data from tpSWAPDEAL (TP ICAP, formerly, Tullett Prebon), the fourth trading venue, used to feed into the assessments of the EUR and GBP ICE Swap Rates.

Clearing House (LCH) from Tradition (UK) Ltd.[19] Receiving and processing further data was not practicable due to the sheer size of the order book, which contains over 30 million messages per day, tenor, and currency. Furthermore, such an endeavor would be unlikely to offer further insights given that, for the period of investigation, Tradition was the market leader in the inter-dealer brokers (IDB) segment, accounting for a market share of over 50%.[20]

All usual order book variables and USD tenors, ranging from 1 to 50 years, are recorded in the data. The period starts on 1 August 2014, when IBA took over the benchmark assessment, and runs to 30 December 2015, a total of 331 trading days.[21] I employ an event study methodology, where 31 March 2015, the effective date of the new benchmark regime, is the event day, d_0. The ISDAFIX regime, referred to as *pre-BRC*, encompasses 160 trading days [d_{-160} = 1 August 2014, d_{-1} = 30 March 2015]. The ICE Swap Rate regime, referred to as *post-BRC*, extends over 171 trading days [d_0 = 31 March 2015, d_{170} = 30 December 2015]. In the data, the 10Y USD swap is on average the most liquid tenor in terms of quote submissions and transactions, and therefore the target of the analysis. I reconstruct the aggregated 10-level full order book at the end of each second, t, during the normal trading hours of the major US exchanges, from 9:30 am to 4 pm New York Eastern Time (ET).

Messages consist of three action types—new order submissions, order changes, and or-

[19] Tradition runs a hybrid model offering voice instruction in conjunction with the LOB. For this study, the electronic LOB data are obtained. Besides this, it is worth noting that Tradition operates two separate order books: one for swaps cleared by LCH and one for those cleared by the Chicago Mercantile Exchange (CME). The LCH order book is the more active of the two by a large margin.

[20] Trading activity estimates are based on information from FCA sources; however, they can also be obtained from industry sources (for example http://www.traditionsef.com/markets/irs/) or the *SEFView* service of Clarus Financial Technology (https://sefview.clarusft.com/).

[21] I exclude holidays, following the IBA Holiday Calendar (https://www.theice.com/iba/holiday-calendars). Moreover, I exclude days when no benchmark rate was assessed, when an early close of US (or UK) exchanges took place, and when trading covered less than 50% of the normal trading hours.

der cancellations—and are timestamped in GMT to the nearest millisecond (ms). Given the USD emphasis, all time references are converted to local ET. Each message is labeled with a unique order identifier, allowing me to follow its life cycle. A message cancellation is recorded following an active cancellation or after a transaction has been concluded. All messages are indexed by a sequence number, providing an audit trail of unfolding events.

Firm and executable quotes, both outright and implied, are recorded and contribute to the ICE Swap Rate assessment. The division between outright and implied orders is commonly employed in the swap market. An outright order is a direct price submission by a trader, for instance in an individual swap contract. An implied order is generated from the price differential between two existing contracts. For example, the differential between the known prices of two swap tenors goes into calculating the unknown value, i.e., the spread between the two, thereby generating a tradable implied order. The Trad-X platform includes an implied engine, which produces a large number of implied orders along the swap curve, substantially enhancing market liquidity.[22] Reports of electronically executed transactions are also obtained.

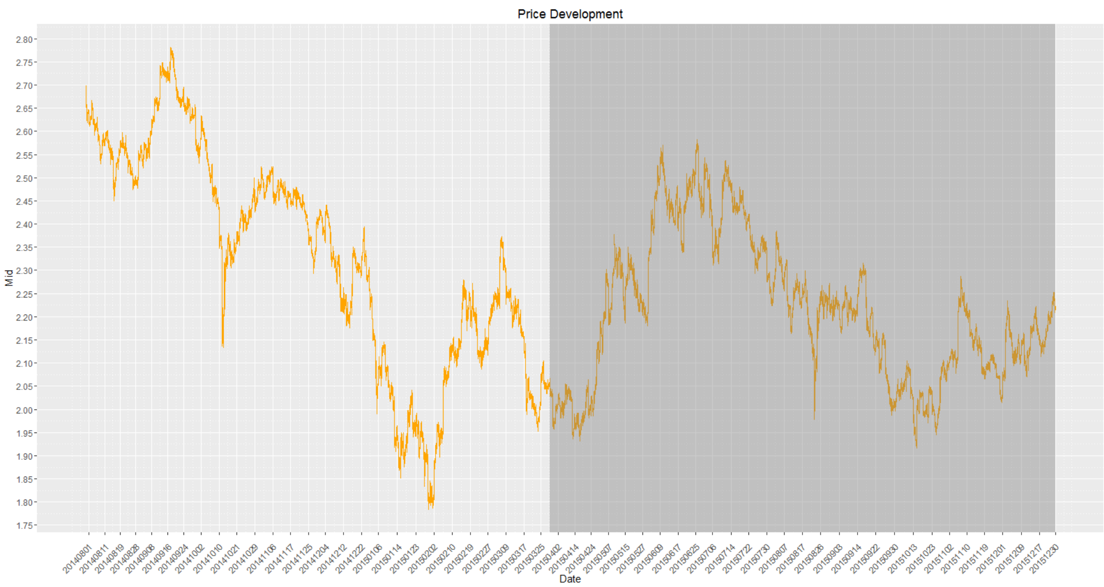
Voice trading and RFQ data are not included in my sample for the inevitable timestamping issues that are bound to arise by trying to merge high-frequency LOB data with lower-frequency voice managed orders and transactions. Moreover, upon an RFQ, the SEF must provide the requester with both the quotes received from responding dealers and the firm resting bid and offer prices on the order book (see Benos et al., 2016, for more details). The requester decides against which quote to execute, and LOB and RFQ prices are therefore expected to be competitive. In addition to the three IDB platforms from which the data for the benchmark assessment is sourced, there are other dealer-to-

[22]The IRS market is characterized by a dynamic swap curve, due to the interaction between different swap tenors via curve spreads and butterflies, and dynamics between the bond and swap markets via swap spreads. Implied orders play a vital role in the continuous pricing of the different products.

client venues such as Bloomberg and Tradeweb. However, according to IBA, the reason that they decided to source data from IDBs was based on the fact that prices on these platforms are firm, while some dealer-to-client platforms operate last-look functionalities and, for this reason, their prices are not considered to be firm. Hence, the dataset obtained from Tradition, the IDB market leader, and consisting of electronically traded swaps, is representative of the market based on which the benchmark is assessed.

The sample period is characterized by price volatility, arguably driven by macroeconomic and political events. Figure 3.2 depicts the midpoint price (where the price of a swap is a percentage rate) of the 10Y USD IRS. The average quoted mid-price for a 10Y USD swap before 31 March 2015 is 2.33 and the average daily price volatility, measured as the standard deviation of the mid-price, during the pre-period amounts to 0.24. After 31 March 2015 (inclusive), the average price and volatility are lower, with values of 2.21 and 0.15 respectively.

Figure 3.2. 10Y USD swap price development



Notes: This figure shows the mid-price development of the 10Y USD IRS over the full sample period from 1 August 2014 to 30 December 2015. The shaded area marks the period of the new benchmark regime from 31 March 2015 to 30 December 2015.

Descriptive statistics of quotes and transactions can be found in Table 3.2 and Table 3.3. The average pre-BRC best bid and offer (BBO) quote size is \$50.66 million, and the post-BRC quote size amounts to \$45.18 million. There is less variability in the submitted BBO quotes after the event date (\$40.52 million versus \$37.14 million). For the 10Y USD swap contract, on an average day, a total of 30.27 million messages are recorded every day, of which 103,000 are outright orders, while the remaining 30.17 million are implied orders accounting for more than 99% of total message flow. Half of the daily messages are new order submissions, while the other half correspond to their respective cancellations. There are very few order changes (an average of two change messages daily), because canceling and replacing a message is faster, and given the paucity of transactions, time priority is less relevant. Total daily messages, as well as daily implied messages, increased jointly by 33%, from 25.89 pre-BRC to 34.37 million in the post-BRC period. Daily outright order submissions also increased, by 26%, from 91,000 pre-BRC to 115,000 post-BRC.

Given the large number of messages, trading on regulated SEFs is characterized by a low trade-to-quote ratio largely driven by the dynamic swap curves generated by Trad-X's implied engine explained above. In particular, transactions can either be directly executed in the individual swap legs, such as the 10Y IRS, or produced via a 'packaged' trade. Packaged transactions, such as swap spreads, curve spreads or butterflies, technically correspond to simultaneous individual transactions in the respective swap legs and are the most frequent. As such, during the full sample period, there were only 165 direct 10Y USD swap trades, averaging less than one transaction per day. However, the daily average combined number of direct and packaged transactions in the 10Y USD swap leg contract on the platform is 21. Overall, this amounts to a total of 6,835 transactions in the 10Y tenor. The average dollar trade size per transaction is a considerable \$54.16 million, leading to a non-negligible daily trading value of \$1.14 billion. Overall, between

Table 3.2. Summary statistics: messages

Price & Quotes	n_D	μ_{MID}	σ_{MID}	μ_{SIZE}	σ_{SIZE}	
Full Sample	331	2.27	0.21	47.80 m	38.89 m	
Pre-BRC	160	2.33	0.24	50.66 m	40.52 m	
Post-BRC	171	2.21	0.15	45.18 m	37.14 m	
Messages	n_{TOTAL}	n_{NEW}	n_{CANCEL}	n_{CHANGE}	$n_{OUTRIGHT}$	$n_{IMPLIED}$
Full Sample	30.27 m	15.14 m	15.14 m	1.90	103.10 k	30.17 m
Pre-BRC	25.89 m	12.94 m	12.94 m	2.17	90.79 k	25.80 m
Post-BRC	34.37 m	17.19 m	17.19 m	1.71	114.63 k	34.26 m
%-Diff	33%	33%	33%	-21%	26%	33%

Notes: This table reports simple descriptive statistics on electronic trading of the 10Y USD IRS on the Trad-X SEF. n_D reports a count of the number of trading days. μ and σ report the arithmetic mean and standard deviation of the mid-price and quote size for orders at the best bid and offer respectively. n reports the average daily count of the total number of messages, new quote submissions, cancellations, changes, outright messages, and implied messages respectively. k and m refer to thousands and millions respectively. *Pre-BRC* refers to the ISDAFIX regime [d_{-160} = 1 August 2014, d_{-1} = 30 March 2015]. *Post-BRC* refers to the ICE Swap Rate regime [d_0 = 31 March 2015, d_{170} = 30 December 2015]. *%-Diff* reports the simple percentage difference between the two periods.

August 2014 and December 2015 a total volume of $370.19 billion was traded electronically in 10Y USD swaps on Trad-X alone. For the rest of this paper, I will consider all transactions in the 10Y IRS, direct executions as well as executions in the leg, as part of packaged trades. Post-BRC, daily transactions increased by 7% from 20 to 22, while the average trade size has remained stable (negligible change from $54.23 million to $54.10 million), and total transactions have grown by 14% from 3,190 to 3,650. The total volume traded likewise expanded from $172.94 billion pre-BRC to $197.25 billion post-BRC, a gain of 14%.

In summary, implied orders dominate, although most of them are canceled without being traded upon, and electronic trades are infrequent but considerable in terms of value. Nevertheless, the firm nature of the quotes ensures their reliability by holding participants accountable for submitted prices. The price discovery process of the market can therefore be compared to the 'tâtonnement' process described in Biais et al. (1995,

Table 3.3. Summary statistics: transactions

	n_{TRANS}	Vol_{TRANS}
Sum	*total*	*total*
Full Sample	6.84 k	370.19 b
Pre-BRC	3.19 k	172.94 b
Post-BRC	3.65 k	197.25 b
%-Diff	14%	14%
Average	*daily*	*per trade*
Full Sample	21.10	54.16 m
Pre-BRC	20.29	54.23 m
Post-BRC	21.80	54.10 m
%-Diff	7%	0%
Median	*daily*	*per trade*
Full Sample	20.00	50.00 m
Pre-BRC	19.00	50.00 m
Post-BRC	21.00	50.00 m
%-Diff	11%	0%

Notes: This table reports descriptive statistics on transactions that were executed electronically on the Trad-X platform. n_{TRANS} reports the number of transactions. Vol_{TRANS} reports the transaction volume. *k*, *m*, and *b* refer to thousands, millions, and billions respectively. *Pre-BRC* refers to the ISDAFIX regime [d_{-160} = 1 August 2014, d_{-1} = 30 March 2015]. *Post-BRC* refers to the ICE Swap Rate regime [d_0 = 31 March 2015, d_{170} = 30 December 2015]. *%-Diff* reports the simple percentage difference between the two periods.

1999), where the order flow in itself is informative, and the efficient price is discovered in a gradual learning process, even when no orders are executed.

IV. The power of benchmarks: Implications for market quality

In order to test the model predictions, I examine the observed effects of the BRC on the quality of the swap benchmark and market. The model contends that an increase in benchmark accuracy through the transition to a transparent market-based assessment and regulatory oversight will have positive effects on the underlying market.

A. A more precise benchmark?

I first analyze whether the benchmark is more accurate, i.e., closer to market fundamentals, by comparing the benchmark rates under the ISDAFIX regime and the IBA regime to market prices available on regulated trading venues. I will analyze the causal role of the regulation in driving these changes in the next section.[23]

To measure changes in the quality of the benchmark, I develop a simple measure termed the benchmark-to-market differential (*BMD*). The ISDAFIX ahead of 31 March 2015 represents the rate at which dealer banks are willing to buy and sell a swap of an SMS (\$50m for 10Y USD IRS) each day before the end of the polling period. The new ICE Swap Rate assessment methodology calculates the benchmark rate by continuously simulating the filling of an SMS order during a two-minute time window. Hence the benchmark rate should be indicative of market conditions and thus act as a representative price for the execution of an SMS trade, both under the ISDAFIX regime and under the ICE Swap Rate Regime.

The *BMD* is simply defined as

$$BMD_{t,d} = |R_d - F_{t,d}| \tag{3.10}$$

where R_d is the assessed benchmark rate on day d and $F_{t,d} = \frac{F^A_{t,d}+F^B_{t,d}}{2}$ is the estimated average of the buy and sell prices for an SMS order at second t, on day d. F^A_t (F^B_t) is the hypothetical execution price for an SMS buy (sell) order simulated for each second t, assuming that an aggressive buyer (seller) crosses the spread and consumes liquidity on the ask (bid) side of the order book.[24] A small differential is interpreted as a benchmark

[23] Note that in this section it is impossible to run difference-in-difference regressions on the *BMD* measure defined in the next paragraph, as no benchmark rate R_d is assessed for the 12Y tenor.

[24] I use hypothetical execution prices because of the lack of enough direct swap trades per day in the 10Y USD IRS. As reported in the descriptive statistics section, over the full period only 165 direct 10Y USD IRS were executed electronically. As a check I also compute the *BMD* based

rate that is indicative of market fundamentals as expressed by the wider market.

The pre and post values in Table 3.4 report the average daily *BMD* during the ISDAFIX and ICE Swap Rate regimes respectively. The pre-BRC and post-BRC regimes differ both in terms of methodologies (panel-based versus market-based) and in terms of assessment lengths (15 versus 2 minutes). For reasons of comparability and robustness, the $BMD_{t,d}$ is averaged over multiple windows of different length (1 min, 10 mins, 30 mins, etc.), centered on the 11 am assessment time and averaged across days within the pre-BRC and post-BRC periods. The different windows allow me to provide a more comprehensive picture of the representativeness of the rate.

For the one-minute window [11:00:00; 11:00:59], the result indicates that an on-platform execution of an SMS order would have, on average, been executed closer to the benchmark rate under the old regime (0.11 bps versus 0.15 bps differential). This difference, however, is likely driven by the differing assessment methodologies. Under the ISDAFIX regime, panel banks submitted point estimates that were concentrated at 11 am and thus, by construction, the difference between the assessed rate and the market price at that point in time will have been small. The ICE Swap Rate, however, is essentially a two-minute average of the market price from 10:58:00 to 11:00:00, introducing stronger price sensitivity, and therefore a larger differential from the market price at 11 am.

Hence, I argue that a comparison of the benchmark rate to the estimated average execution price, for different time windows centered on 11 am, is most meaningful. By extending the window length over which the *BMD* measure is computed, I find that post-BRC the benchmark rate is indicative of market prices for an extended period. For the 4 mins, 10 mins, 20 mins, 30 mins, and 60 mins comparisons, the *BMD* is 3% to 12% lower under the new regime than the old regime. Based on the 10-minute window, the

on the few executed transactions and find a qualitatively similar result.

Table 3.4. Benchmark-to-market differential

Window	Time	Pre-BRC	Post-BRC	t-Stat	%-Diff
1 min	[11:00:00; 11:00:59]	0.11	0.15	3.65***	37.19%
4 mins	[10:58:00; 11:01:59]	0.14	0.13	-1.55	-9.68%
10 mins	[10:55:00; 11:04:59]	0.22	0.19	-2.24**	-12.01%
20 mins	[10:50:00; 11:09:59]	0.29	0.27	-1.5	-7.72%
30 mins	[10:45:00; 11:14:59]	0.35	0.34	-0.56	-2.87%
60 mins	[10:30:00; 11:29:59]	0.48	0.46	-0.67	-3.41%
10 mins before	[10:48:00; 10:57:59]	0.35	0.30	-2.15**	-14.71%
10 mins after	[11:00:00; 11:09:59]	0.30	0.31	0.55	4.02%
Assessment end	[11:15] & [11:00]	0.48	0.15	-9.83***	-68.07%
Publication	[11:30] & [11:15]	0.66	0.52	-2.72***	-21.79%

Notes: This table reports the *BMD* before and after the BRC. I average the $BMD_{t,d}$ over different windows around the 11 am assessment. The *Assessment end* window, captures the average differential during the full minute after the respective assessment end times of the old [11:15:00; 11:15:59] and new [11:00:00; 11:00:59] regimes. The *Publication* window, captures the average differential during the full minute after the respective publication times of the old [11:30:00; 11:30:59] and new [11:15:00; 11:15:59] regimes. *Pre-BRC* refers to the ISDAFIX regime [d_{-160} = 1 August 2014, d_{-1} = 30 March 2015]. *Post-BRC* refers to the ICE Swap Rate regime [d_0 = 31 March 2015, d_{170} = 30 December 2015]. All values are expressed in bps (1 bps = 0.01%). The t-value is the statistic of a two-sample t-test of $\mu_1 - \mu_2 = 0$. *, **, and *** correspond to statistical significance at 10%, 5%, and 1% levels respectively. *%-Diff* reports the simple percentage difference between the two periods.

hypothesis that the BRC did positively affect the representativeness of the benchmark rate is accepted at the 5% significance level. Moreover, the *BMD*s at the respective assessment ends and publication times of the ISDAFIX and ICE Swap Rate regimes are substantially smaller under the new benchmark regime (reductions of 68% and 22% respectively)—results, which are statistically significant at the 1% level. The 10-minute window immediately preceding the start of the benchmark assessments is supportive of a more accurate benchmark too. The market price should be indicative of how dealers value an SMS swap at the time of the assessment, and the quote submissions ahead of the assessment start should thus reflect the upcoming benchmark rate. With a mean value of 0.35 bps versus 0.30 bps, the average daily *BMD* during the 10-minute window [10:48:00; 10:58:00] is 15% smaller at the 5% significance level during the post-BRC period.

The results presented in Table 3.4 are, therefore, in line with the model, suggesting that an increase in price accuracy reduces the noise in the benchmark (σ). Specifically, I show that the ICE Swap Rate more precisely reflects market conditions at the end of the assessment.

B. A more efficient price?

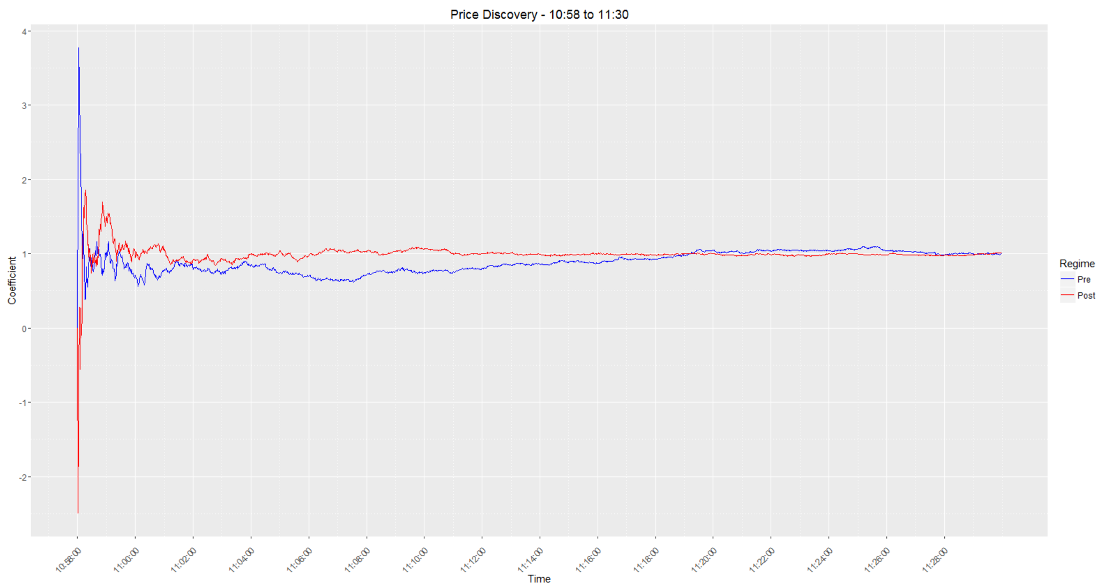
Equation 3.8 suggests that the verified reduction of noise in the benchmark should also translate to a decline in the noise in prices. Hence, to test the informational efficiency of market prices, I estimate 'unbiasedness regressions' consistent with Biais et al. (1995, 1999). The level of price efficiency for the 10Y swap is computed for both the pre-BRC and post-BRC periods through separate estimations of Equation 3.11 and the averaging of the slope coefficients across seconds t.

$$r_{oc} = \alpha + \beta r_{ot} + \epsilon_{ot} \tag{3.11}$$

where r_{oc} is the open-to-close return for the time period of interest and r_{ot} is the return from the opening of the chosen period to the second t. Since my interest lies in the benchmark assessment period, I define the open and close to be 10:58:00 and 11:30:00 respectively. According to Biais et al. (1995, 1999), β measures the signal-to-noise ratio. Since the observable return consists of the true return and some noise element (Barclay and Hendershott, 2003; Ibikunle, 2015), a coefficient close to one suggests informationally efficient prices, while a coefficient smaller than one is consistent with noisier prices. A coefficient bigger than one may be driven by stale prices.

Figure 3.3 reports the average slope coefficient estimates for the unbiasedness regressions. As expected, during the first few intervals of the estimation window, the returns from 10:58:00 to interval t do not explain the total '10:58:00–11:30:00' return well. Still, as time progresses, it becomes apparent that noise decreases rapidly and the swap price

Figure 3.3. Price efficiency around the benchmark assessment



Notes: This figure shows the price efficiency of the 10Y USD IRS between 10:58:00 and 11:30:00. Timestamps are in ET. The blue line shows the price efficiency during the ISDAFIX regime [d_{-160} = 1 August 2014, d_{-1} = 30 March 2015]. The red line shows the price efficiency during the ICE Swap Rate regime [d_0 = 31 March 2015, d_{170} = 30 December 2015]. The coefficient β measures the signal-to-noise ratio. A coefficient close to one suggests informationally efficient prices. A coefficient smaller than one is consistent with noisier prices. A coefficient bigger than one may be driven by stale prices.

efficiency improves continuously. Under the ICE Swap Rate regime, informational efficiency is achieved faster than under the ISDAFIX regime, as the coefficient quickly converges to unity and remains at that level. Returns from the pre-BRC period indicate that swap prices are noisier (as indicated by coefficient values below one) and informational efficiency takes longer to achieve. By means of example, β reaches approximately unity at 11:04:00 in the post-BRC regime (red line), while it only achieves similar levels roughly 15 minutes later in the pre-BRC regime (blue line). Overall, the results suggest that, in the post-BRC period, price efficiency is enhanced compared to the pre-BRC period.

C. A more liquid market?

I have demonstrated that in the post-BRC period the benchmark is more accurate and prices are less noisy. Equation 3.9 predicts that the expected demand should be affected too. Instead of structurally estimating the demand of each dealer, I measure market liquidity and use it as a proxy to verify this model prediction. The intuition here is that market liquidity is enhanced when demand for trading rises. Since liquidity is not jointly determined with signed order imbalances, concurrent increases in buys and sells are expected, which should enhance the probability of timely order execution (Chordia et al., 2008). I focus on five metrics to measure market liquidity.

The first is the quoted dollar spread (QS) and it is defined as the difference between the best bid and offer prices, computed for each second t:

$$QS_t = (A_t - B_t) \tag{3.12}$$

Secondly, the relative quoted spread (RQS) is computed, defined as the ratio of the quoted spread and the quoted mid-price (M_t). The relative spread is sensitive to movements in the market price, which in this case is volatile and on average lower during the post-BRC period (see Table 3.2). Hence, this measure is used only to corroborate the results, since a lower price should lead to a larger relative spread if quoted spreads remain constant.

$$RQS_t = \frac{(A_t - B_t)}{M_t} \tag{3.13}$$

The third and fourth liquidity proxies exploit market depth. They are the quoted depth (QD) and 10-level quoted depth ($QD10$), and are defined as the sum of the offer volume (V_t^A) and the bid volume (V_t^B) at second t at the best level and the best ten levels ($l = 1, ..., 10$) of the order book respectively:

$$QD_t = (V_t^A + V_t^B) \tag{3.14}$$

$$QD10_t = \sum_{l=1}^{10} (V_{l,t}^A + V_{l,t}^B) \tag{3.15}$$

Finally, I also develop an additional measure of the spread, which I call the 'fill spread'. The measure is useful in markets characterized by a LOB with active quoting but very few transactions, such as the one I am examining.[25] The hypothetical fill spread (FS) measure aims to approximate the effective spread. Typically, the effective spread is computed as $2 \times DIR_t \times (P_t - M_t)$, where DIR_t is a directional parameter accounting for buyer-initiated and seller-initiated transactions and P_t is the transaction price. A trader could either buy or sell an SMS swap of \$50m. Since I simulate the filling of both a buy (F_t^A) and a sell (F_t^B) SMS order for each second against existing orders on the book, DIR_t is immaterial. The hypothetical fill spread can thus be written as

$$FS_t = (F_t^A - M_t) + (M_t - F_t^B) \tag{3.16}$$

As the comparisons to the mid-price in Equation 3.16 cancel out, however, this can be written as the difference between F_t^A and F_t^B as in Equation 3.17.

In other words, the fill spread measures the roundtrip costs of completing a buy

[25] As reported in the descriptive statistics section, only 165 direct swap trades are executed in the 10Y USD IRS. Further complicating the matter is the fact that, of the total of 6,835 10Y USD IRS trades, for example, swap spread transactions (i.e., trading the differential between the bond yield and swap rate) are priced against the bond yield. Hence, the transaction price determined for the 10Y USD swap usually falls within the BBO spread of the order book. This makes it impossible to calculate effective spread measures for individual swap leg transactions of packaged trades directly. I thus compute the volume-weighted effective spread ($VWES$) for the few electronically executed direct swap transactions. The mean value of the $VWES$ for the pre-BRC period amounts to 0.3 bps, while it is 0.27 bps for the post-BRC period. This corresponds to a reduction of 10%, in line with the results in Table 3.5.

transaction and a sell transaction, approximating the liquidity on both sides of the order book at second t. Since quote sizes at the best level (and beyond) vary and commonly account for less than the \$50m standard trade size, the fill spread is an aggregate measure accounting for both the prevailing spread and depth of the order book. Hence, my view is that this is the best measure of liquidity for my purposes.

$$FS_t = (F_t^A - F_t^B) \tag{3.17}$$

All measures are time-weighted (TW), as shown in the following equation, where LM_t represents one of the above-described liquidity measures. t is the second timestamp of the $i = 1, ..., N$ intraday quote update on day d. T is the length of the trading day.

$$TWLM_t = \frac{1}{T}\sum_{i=1}^{N} LM_t(t_{i+1} - t_i) \tag{3.18}$$

Table 3.5 reports the long-term comparison of the liquidity measures by splitting the sample period into the periods before and after the exogenously determined event date (please refer to the robustness section for the short-term liquidity effects). I report three spread measures and two market depth measures. Quoted spreads and relative quoted spreads are both significantly lower in the post-BRC period. The average daily time-weighted quoted spread ($TWQS$) decreases from 0.7 bps to 0.6 bps, a reduction of 14%. Similarly, the average daily time-weighted relative quoted spread ($TWRQS$), which accounts for fluctuations in the price, narrows from 0.31 bps to 0.27 bps, a drop of 11%. The improvement in the time-weighted average spread measures is significant at the 1% level. Variations in the width of the spread measures reduce after the BRC, with the average daily standard deviation declining by between 34% and 37%. The results also hold if I use daily median values.

The spread analysis is complemented by a study of market depth, both at the best bid

Table 3.5. Quoted liquidity under the ISDAFIX and ICE Swap Rate regimes

	Spreads			Depth	
	TWQS	*TWRQS*	*TWFS*	*TWQD*	*TWQD10*
Mean					
Pre	0.70	0.31	0.78	100.81 m	3.39 b
Post	0.60	0.27	0.70	90.56 m	3.52 b
t-Stat	-6.76***	-4.21***	-5.65***	-4.54***	1.5
%-Diff	-14.34%	-10.96%	-11.24%	-10.17%	3.94%
Median					
Pre	0.67	0.29	0.74	89.20 m	3.52 b
Post	0.60	0.27	0.68	79.27 m	3.65 b
t-Stat	-6.03***	-3.15***	-5.89***	-4.35***	1.41
%-Diff	-10.82%	-7.27%	-8.42%	-11.13%	3.90%
Std Dev					
Pre	0.17	0.08	0.16	51.72 m	0.79 b
Post	0.11	0.05	0.10	47.03 m	0.72 b
t-Stat	-3.58***	-3.23***	-3.17***	-3.46***	-2.39**
%-Diff	-36.71%	-34.35%	-33.52%	-9.08%	-9.63%
Count			*Non-fill of an SMS order*		
Pre			885		
Post			326		
%-Diff			-63%		

Notes: This table reports the long-term comparison of the liquidity variables before and after the BRC. *TWQS* reports the spread in absolute dollar terms. *TWRQS* reports the ratio of the quoted spread to the mid-price. *TWFS* reports the difference between the hypothetical execution price of an SMS trade on both sides of the book as per the methodology section. *TWQD* is the sum of the depth at the best bid and offer prices. *TWQD10* is the sum of the depth at the bid and offer sides of the 10-levels of the order book. All liquidity measures are computed as daily averages (medians) and then averaged across the period of interest. The median captures the weighted median (by number of occurrence) of the liquidity measures. Standard deviation reports the average daily standard deviation of the liquidity measures. I also count the number of times that an SMS order cannot be completed (on a second-by-second basis) on either side of the book. *Pre-BRC* refers to the ISDAFIX regime [d_{-160} = 1 August 2014, d_{-1} = 30 March 2015]. *Post-BRC* refers to the ICE Swap Rate regime [d_0 = 31 March 2015, d_{170} = 30 December 2015]. All spread measures are expressed in bps (1 bps = 0.01%). *m* and *b* refer to millions and billions respectively. The t-value is the statistic of a two-sample t-test of $\mu_1 - \mu_2 = 0$. *, **, and *** correspond to statistical significance at 10%, 5%, and 1% levels respectively. *%-Diff* reports the simple percentage difference between the two periods.

and best offer level, as well as at the bids and offers across ten levels of the order book. Columns four and five of Table 3.5 report the results for the time-weighted quoted depth measures. On the one hand, average daily quoted depth is lower during the post-BRC period ($100million versus $90million), a deterioration of 10% at the 1% significance level. On the other hand, 10-level quoted depth increases marginally, from an average daily value of $3.39 billion pre-BRC to $3.52 billion post-BRC. However, this 4% increase in *TWQD10* is not statistically significant. Again, the results are consistent when I use median values.[26]

In short, spreads narrow and the order book at the first ten levels becomes marginally deeper, but depth at the best level becomes thinner. Traders, however, are interested in the costs of trading. Consequently, the third column of Table 3.5 reports the results for the time-weighted fill spread (*TWFS*)—the aggregate measure of the simultaneous impacts on spreads and depth. Average (median) daily fill spreads on the Trad-X platform in the post-BRC period narrow from 0.78 (0.74) bps to 0.7 (0.68) bps, a decrease of 11% (8%) at the 1% significance level. This result shows that it is cheaper to trade electronically under the ICE Swap Rate regime. Also, the total number of times that an SMS order cannot be completed (on a second-by-second basis) on the Trad-X platform on either side of the book due to missing liquidity decreases from 885 in the pre-BRC period to 326 in the post-BRC period. This corresponds to a drop of 63%. The finding is indicative of a more resilient order book, with traders confidently posting executable quotes.

D. Regulation as a driver?

Thus far I have provided evidence, based on the measurement of market quality factors, that the condition of the swap market improved after the FCA started regulating the relevant benchmark, but I cannot infer that the regulation caused the changes. In this section I attempt to link the observed improvements in market quality to the benchmark regulation by employing a difference-in-difference (DiD) approach. Specifically, I compare the changes in liquidity for tenors with a regulated benchmark assessment

[26] For robustness, I compute an alternative measure of order book depth by simulating the continuous filling of a large transaction (several multiples of the 10Y SMS). I find a highly significant improvement in execution costs for large and very large transactions too. The results can be found in Table A.4 of Appendix XI.

vis-à-vis those without one by estimating the following regression model:

$$DV_{i,d} = \alpha + \beta_1 Event_d + \beta_2 Treatment_i + \beta_3 Event_d \times Treatment_i + \gamma' X_d + \mu_i + \epsilon_{i,d} \quad (3.19)$$

where i denotes tenors and d denotes days. The dependent variable DV corresponds to one of the two liquidity measures: *TWQS* or *TWFS*. I focus on these measures as the fill spread accounts for the aggregated effect on spreads and depth and reports the net effect.[27] *Event* is a dummy taking the value 0 for the pre-BRC period [d_{-160} = 1 August 2014, d_{-1} = 30 March 2015] and 1 for the post-BRC period [d_0 = 31 March 2015, d_{170} = 30 December 2015]. *Treatment* is a dummy taking the value 1 for tenors which are part of the treated group and zero otherwise. The treated group is made up of tenors for which a benchmark is assessed. These tenors are therefore covered by the regulatory regime and benefit from the increased benchmark precision following the BRC. For the results reported here, the tenor chosen for the treatment group is the 10Y USD IRS, and the tenor chosen for the control group is the 12Y USD IRS. No benchmark rate is assessed for the 12Y tenor (see Table 3.1) and it is the most actively quoted and traded non-benchmark MAT tenor in the data.[28] X_d is a vector of control variables including swap and debt market volatility, venue participation, quoting and trading behavior, and macroeconomic developments. β_1 captures any common effects that might have impacted all swap tenors following the BRC. β_2 absorbs any pre-existing differences in characteristics between the treatment and control groups. The coefficient of interest

[27]The *TWQD* and *TWQD10* specifications of the DiD panel regressions can be found in Table A.5 of Appendix XI.

[28]Due to spillover effects caused by the close interaction of the swap curve, the control group is not completely untreated. However, this means that my estimates are conservative. For robustness purposes, I also run the DiD regressions using multiple tenors, where the 5Y and 10Y tenors form the treatment group and the 11Y and 12Y the control group—again chosen based on their liquidity profile. The findings are confirmed, but I do not report these results in the main paper because the 11Y tenor is not a MAT swap. The regression results, time series, and structural breaks of the 5Y, 11Y, and 12Y liquidity measures can, however, be found in the FCA Occasional Paper 27 and are available on request.

is β_3, which captures the interaction of *Event* and *Treatment* and thus estimates any incremental effects of the BRC. Hence, β_3 reflects the change in liquidity for tenors that are part of the benchmark regime compared to the change in liquidity for tenors that are not. The model is estimated using tenor fixed effects.

Table 3.6 reports the estimation results. The DiD model is estimated under various iterations, excluding and including control variables (labeled as [1] and [2] respectively). The results show that there is little difference in the coefficients of interest between the two specifications. Overall, the control variables help to explain a significant proportion of the evolution of the liquidity measures, with adjusted R^2 of 67% and 56% for the regression models in which the dependent variables are $TWQS$ and $TWFS$ respectively.

Table 3.6. Difference-in-difference panel regressions for spread measures

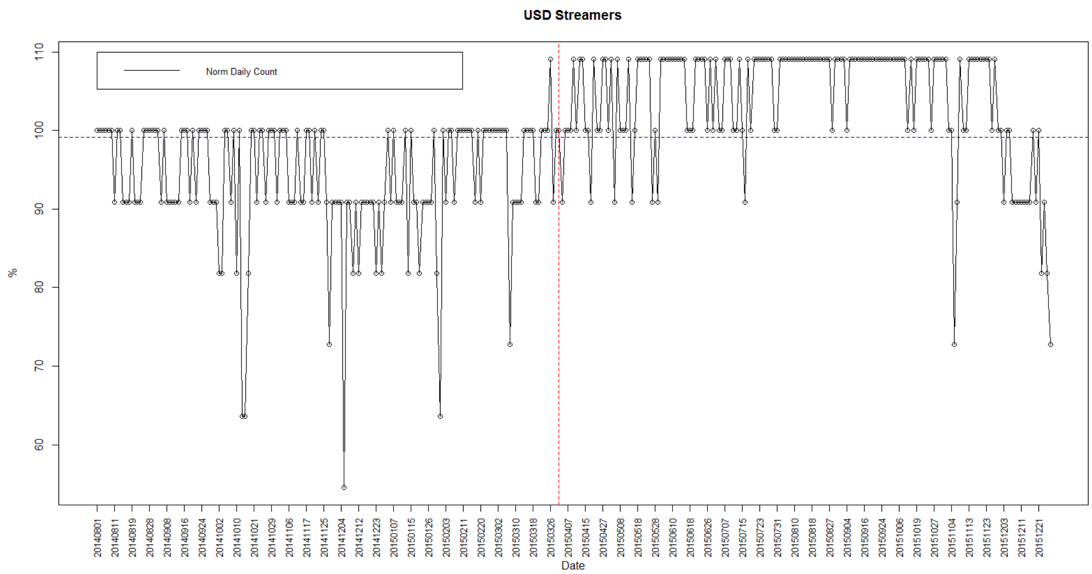
	TWQS				*TWFS*			
	(1)		*(2)*		*(1)*		*(2)*	
	Coeff	*t-Stat*	*Coeff*	*t-Stat*	*Coeff*	*t-Stat*	*Coeff*	*t-Stat*
Constant	6.78E-03	32.82***	2.03E-02	9.03***	7.35E-03	45.83***	2.35E-02	11.3***
Event	-6.35E-04	-2.85***	-1.34E-04	-0.76	-2.00E-04	-1.1	3.45E-04	2.11**
Treatment	2.40E-04	4.24***	2.37E-04	4.15***	4.89E-04	4.66***	4.91E-04	4.64***
Interaction	-3.71E-04	-4***	-3.57E-04	-3.94***	-6.80E-04	-5.65***	-6.83E-04	-5.62***
SRVIX			1.10E-02	1.26			7.07E-03	0.82
TYVIX			-1.45E-03	-0.92			-2.68E-04	-0.19
MESS_10Y			4.60E-04	2.38**			5.25E-04	2.59***
MESS_12Y:10Y			-1.25E-04	-0.53			-2.56E-04	-1.31
TRANS_10Y			-6.14E-08	-0.01			8.80E-06	0.11
TRANS_12Y:10Y			-2.47E-05	-0.42			-1.45E-05	-0.27
PARTICIPANTS			-2.61E-03	-2.74***			-3.91E-03	-3.72***
MACRO			4.21E-03	8.78***			2.90E-03	6.26***
O:I_10Y			1.68E-03	5.2***			1.67E-03	5.39***
Adj R^2	8.57%		67.28%		6.37%		56.07%	
N	658		637		658		637	
Specification	FE		FE		FE		FE	

Notes: This table reports the results of the DiD panel regression model specified in Equation 3.19 using *TWQS* and *TWFS* as dependent variables. *(1)* presents the DiD model without controls while *(2)* presents the same specification with controls. *Event* is a dummy variable that takes the value 0 for the pre-BRC period [d_{-160} = 1 August 2014, d_{-1} = 30 March 2015] and 1 for the post-BRC period [d_0 = 31 March 2015, d_{170} = 30 December 2015]. *Treatment* is a dummy that takes the value 1 for benchmark-grade swaps (10Y) and 0 otherwise (12Y). *Interaction* is a dummy variable computed as $Event \times Treatment$. *SRVIX* is the log return on the Interest Rate Swap Volatility Index. *TYVIX* is the log return on the 10-year US Treasury Note Volatility Index. $MESS\_10Y$ is the log daily count of the number of messages received by the platform operator for the 10Y IRS contract. $MESS\_12Y : 10Y$ is the log ratio of messages for the 12Y contract relative to the 10Y contract. $TRANS\_10Y$ is the log daily number of transactions in the 10Y IRS contract. $TRANS\_12Y : 10Y$ is the log ratio of the number of transactions in the 12Y contract relative to the 10Y contract. *PARTICIPANTS* represents the log number of USD streamers per trading day. *MACRO* is a dummy variable that takes the value 1 on days with macroeconomic announcements by the Federal Open Market Committee (FOMC) and the Governing Council of the ECB and 0 otherwise. *O:I_10Y* is the log ratio of outright to implied messages in the 10Y IRS contract. The models are estimated using tenor fixed effects. We use Driscoll and Kraay (1998) consistent standard errors. Robust t-statistics are shown in the *t-Stat* columns. *, **, and *** correspond to statistical significance at 10%, 5%, and 1% levels respectively. Sample period is 01.08.2014-30.12.2015.

Firstly, with the BRC there is an improvement in *TWQS* for both groups of swap tenors (10Y and 12Y), as indicated by the negative and highly significant *Event* coefficient. Importantly, however, the significant *Interaction* term shows that the enhancement in *TWQS* for the 10Y tenor is greater than the improvement in the 12Y tenor. The *Interaction* coefficient for *TWFS* indicates that the execution costs for the 10Y USD IRS have also come down significantly, and crucially by more than those for the 12Y USD IRS, following the change in benchmark assessment methodology and the regulation by the FCA. The results are equally strong irrespective of whether I include multiple controls in the model specifications, suggesting that the liquidity improvement is over and above the other effects driving swap market liquidity.

Both the quoted spread and the fill spread for all swaps widen insignificantly on days with a surge in IRS volatility (*SRVIX*), and narrow insignificantly on days with a rise in U.S. Treasury note volatility (*TYVIX*). An increase in quoting activity (*MESS_10Y*), however, translates into significantly narrower spreads and execution costs. Trading activity (*TRANS_10Y*) has an inconsistent and mostly negligible effect on liquidity. The ratios of messages (*MESS_12Y:10Y*) and transactions (*TRANS_12Y:10Y*), proxying for a change in the liquidity pattern between the 12Y and 10Y tenors, do not affect the liquidity measures. The number of USD streamers (*PARTICIPANTS*), depicted in Figure 3.4, has a strongly positive effect on the liquidity metrics. An increase in the number of participants on the trading venue around the event date leads to a sharp and highly significant reduction in quoted spreads and fill spreads. This aligns with the assertion that increased on-platform participation leads to a liquidity improvement, which is consistent with empirical market microstructure findings (see for example Barclay and Hendershott, 2004). Unsurprisingly, macroeconomic announcement days (*MACRO*) are characterized by a significant widening of spreads and inflation of execution costs—in line with expectations, due to the increase in uncertainty on such days. Finally, a change in the ratio of outright to implied orders ($O{:}I\_10Y$), for example due to a reduction in implied quotes and therefore an increase in the ratio, leads to a widening of spreads.

Figure 3.4. USD participants



Notes: This figure shows the development of the daily count of USD streamers on the Trad-X platform over the sample period. The numbers are normalized and presented in percentage terms (%). The blue dotted line depicts the long-term average of the time series. The red dotted line marks the event date [d_0 = 31 March 2015]. *Pre-BRC* refers to the ISDAFIX regime [d_{-160} = 1 August 2014, d_{-1} = 30 March 2015]. *Post-BRC* refers to the ICE Swap Rate regime [d_0 = 31 March 2015, d_{170} = 30 December 2015].

Importantly, even after controlling for a multitude of potentially confounding effects, the findings show a significant incremental improvement in on-platform execution costs for benchmark-grade swaps. Taken together, the results suggest that the liquidity improvement is driven by the exogenous regulatory change and methodological evolution of the benchmark, and therefore confirm my hypothesis and the predictions of the model. The effects of the regulation are economically significant too. The costs savings, as measured by the total effect of the BRC on electronically executed 10Y USD swaps on the Trad-X platform alone, amount to between \$3.33 million and \$9.92 million.[29] The

[29] The total effect cost savings are computed following the rationale in Benos et al. (2016), but adjusted to this paper's setting: $\Sigma_{i=1,3} \frac{\beta_i}{100 \times 2} \times Vol_{POST} \times Mat$, where β_i are the coefficients

marginal cost savings, computed on the basis of the incremental reduction in execution costs of the 10Y benchmark-grade swap tenor over the 12Y non-benchmark-grade tenor, range between \$3.6 million and \$6.7 million. Given that the focus lies on one tenor only and that the swaps can be traded on other venues too, the overall benefits are likely to be substantially larger.

V. Robustness tests

A. Short-term liquidity effects

The previous sections compare the market liquidity before and after the regime change by exogenously identifying the potential break date. However, changes in the microstructure of the underlying market could have occurred before or after the event date. I therefore use the event study methodology employed in Hegde and McDermott (2003) to assess the validity of the reported results. I calculate the liquidity measures over different time intervals surrounding the event date of 31 March 2015 and compute a ratio by comparing them to the long-term average of the estimation window [d_{-160} = 1 August 2014, d_{-30} = 13 February 2015], which extends to thirty trading days before the regime change, and represents a period that is unlikely to have been affected by the BRC. If the ratio of the liquidity measure for some interval in Table 3.7 is greater (smaller) than unity, it indicates that the interval average is greater (smaller) than the estimation window average. Given the similarity of the findings for the three spread measures in Table 3.5, I only discuss the $TWQS$ here.

from Equation 3.19. I divide by *100* because swap prices are quoted as a percentage rate, and further divide by *2* to indicate the cost savings of a one-directional trade. Vol_{POST} is the sum of the electronic volume traded in the 10Y USD IRS contract following the BRC (197.25 billion, as reported in Table 3.3), and *Mat* is the maturity of the contract (10 years). For the marginal effect cost savings, only the estimated coefficient of the interaction term (β_3) is used. The cost savings represent the present value (assuming a zero risk-free rate) of the decreased future fixed rate payments of a swap with a notional value amounting to Vol_{POST}.

Table 3.7. Short-term liquidity reaction to the benchmark regime change

	TWQS		*TWQD*		*TWQD10*	
Interval	*Mean (Median)*	*t-Stat*	*Mean (Median)*	*t-Stat*	*Mean (Median)*	*t-Stat*
[0; 0]	0.87	-	1.03	-	1.27	-
	(0.94)	-	(0.92)	-	(1.29)	-
[-1; +1]	0.87	-37.68***	0.95	-1.22	1.05	0.29
	(0.94)	-	(0.94)	-3.38*	(1.07)	0.42*
[-2; +2]	0.88	-10.62***	0.98	-0.35	1.13	1.21
	(0.94)	-	(0.96)	-0.77*	(1.13)	1.25*
[-3; +3]	0.90	-3.48**	1.00	0.05	1.16	1.75
	(0.97)	-1.15	(1.01)	0.3*	(1.15)	1.76*
[-4; +4]	0.92	-3.09**	0.99	-0.13	1.12	1.5
	(0.96)	-1.77	(1.01)	0.13*	(1.10)	1.19*
[-5; +5]	0.92	-3.36***	1.01	0.18	1.12	1.71
	(0.96)	-2.38**	(1.02)	0.43*	(1.11)	1.43*
[-10; +10]	0.97	-0.53	1.03	0.74	1.09	1.56
	(0.98)	-0.66	(1.06)	1.67*	(1.07)	1.11*
[-20; +20]	0.96	-1.55	1.06	2.17**	1.09	2.5**
	(0.98)	-1.12	(1.09)	3.12***	(1.08)	2.15**
[-30; +30]	0.98	-0.64	1.04	1.82*	1.05	1.84*
	(0.98)	-1.04	(1.06)	2.31**	(1.05)	1.51*
[-30; -1]	1.08	1.43	1.09	2.9***	0.99	-0.23
	(1.03)	1.19	(1.12)	3.36***	(0.97)	-0.72*
[+1; +30]	0.89	-5.45***	0.99	-0.39	1.11	2.98***
	(0.94)	-3.04***	(1.01)	0.16*	(1.12)	3.28***

Notes: This table reports the short-term reaction of the liquidity variables around the BRC. *Interval* represents the time period, in number of days $d \varepsilon D$, before and after the event date [d_0 = 31 March 2015], over which the liquidity measures are averaged. *TWQS* reports the spread in absolute dollar terms. *TWQD* is the sum of the depth at the best bid and offer prices. *TWQD10* is the sum of the depth at the bid and offer sides of the 10-levels of the order book. All liquidity measures are computed as daily averages (medians) and then averaged across the intervals of interest. The ratios are computed relative to a reference value, which is the average of the same liquidity measure over the estimation window [d_{-160} = 1 August 2014, d_{-30} = 13 February 2015]. All values are ratios. The t-value is the statistic of a one-sample t-test of $\mu = 1$. *, **, and *** correspond to statistical significance at 10%, 5%, and 1% levels respectively. '–' is reported when the significance could not be assessed due to the small sample size of the interval.

The ratio obtained using the average (median) time-weighted quoted spread for the interval [0; 0], covering only the event date of 31 March 2015, is 0.87 (0.94), i.e., considerably below its long-term average. For the first five intervals ([-1; +1], [-2; +2], [-3; +3], [-4; +4], [-5; +5]) centered on the event date, the average daily *TWQS* ratio indicates that the spreads are significantly lower (at the 5% to 1% level) than their long-term average. During the 11-day interval [-5, +5] centered on the event date, average as well as median spreads are significantly lower, with values of 0.92 and 0.96, at the 1% and 5% significance levels respectively. The results for longer time periods are insignificant. Importantly, the findings for the intervals [-30; -1] and [+1; +30] demonstrate that the narrowing of spreads is driven by a significant decrease in the post-BRC period rather than the pre-BRC period, as shown by the ratio of 0.89 at the 1% significance level versus the insignificant ratio of 1.08 for the post-BRC and pre-BRC periods respectively.

Since the earlier long-term results on depth were less clear-cut, the event study findings on *TWQD* and *TWQD10* are of particular interest. The average time-weighted quoted depth at the best level is above its long-term average on the event date [0; 0] itself (1.03), although its median is below unity and further drops significantly below the estimation window reference value for the intervals [-1; +1] and [-2; +2]. The interval [-30; -1] shows that *TWQD* is above its long-term average (1.09) at the 1% significance level ahead of the BRC. During the thirty days [+1; +30] after the BRC, quoted depth (ratio of 0.99) is not significantly different from the reference value of the estimation window. Regarding the average 10-level quoted depth, the book is much deeper on the event date [0; 0] with a value of 1.27. The [-30; -1] interval shows that the thirty days before the regime change are characterized by a slightly thinner order book (median ratio of 0.97 at the 10% significance level). The [+1; +30] period, however, shows a deeper order book (highly significant average ratio of 1.11 and median ratio of 1.12). The event study confirms the earlier findings suggesting that market liquidity has reacted to the BRC, and done so positively.

B. Structural breaks

Thus far I have relied on an exogenous determination of the event date to assess the implications of the BRC for liquidity. Specifically, the measures were computed before and after the changes were introduced to the methodology and the benchmark was regulated. In this subsection, I statistically determine structural breaks in the liquidity measures, endogenously. I follow the approach of Bai and Perron (1998, 2003, BP), the application of which is described in detail in Zeileis et al. (2003). The model set-up is based on a standard linear regression of the form

$$y_d = x_d^D \beta_d + \mu_d \quad (d = 1, ..., n) \tag{3.20}$$

where y_d and x_d correspond to the values of the dependent and explanatory variables respectively on day d. β_d is the regression coefficient, which can vary over time. The model tests the null hypothesis that the coefficient remains constant over time, versus the alternative of a change in the coefficient over time:

$$H_0 : \beta_d = \beta_0 \quad (d = 1, ..., n) \tag{3.21}$$

The method assumes that there are m breakpoints in the time series at which points the mean of the coefficient moves from one long-term level to another. Hence, the set of breakpoints, which are unknown, must be endogenously estimated. m breakpoints imply *m+1* segments with a constant coefficient. Based on Bai and Perron (2003), in order to date the structural changes, a dynamic programming algorithm is used to compare different combinations of m-partitions to achieve a minimum global residual sum of squares. The process sequentially examines the partition of *m+1* versus m breaks and compares which of the partitions provides the overall minimal residual sum of squares compared to one additional segment.

In this case, I apply a pure structural change model, and I test whether the mean of the liquidity measure in question changes over the course of the sample period. To do so, a constant is fitted to the time series data of the dependent variable. A trimming factor of 15% (as suggested by Bai and Perron, 2003) is applied, allowing for a maximum of five breaks. The trimming factor determines the minimum number of observations in each segment. Since the sample consists of 331 trading days, the trimming value implies that each segment is required to have at least 49 observations. I determine the optimal number of breaks as in Zeileis et al. (2003).

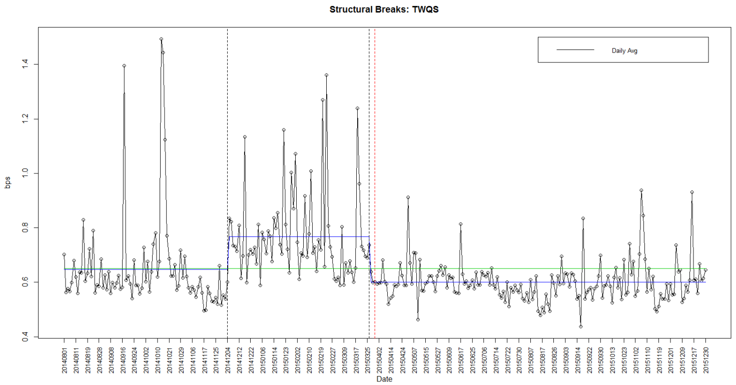
Figure 3.5 depicts the determined structural changes in the time series of the four different liquidity measures. The *TWQS*, *TWFS*, and *TWQD10* experience two breaks each, while the *TWQD* shows three breaks. The common pattern that can be established is that, for each of the four liquidity measures, one break occurs very shortly before the BRC. For both spread measures, the multiple structural break models indicate a first break (upward) in the data on 4 December 2014. I have identified two potential reasons for this change: (i) European Central Bank (ECB) president Mario Draghi announcing a potential quantitative easing intervention and (ii) a drop in the number of USD streamers on the trading venue. On 5 December 2014, the number of dealers on the platform falls by roughly 45% (see Figure 3.4), which could also be the cause of the observed widening of spreads. The number of dealers recovers to its previous level on the next day and stays relatively stable after that but, clearly, liquidity does not recover. However, participation over the following days is volatile, possibly explaining the wider spreads throughout the period from December to March. The second downward break occurs on 26 March 2015, three trading days before the BRC.[30] Given the proximity to the event date (31 March 2015) and the fact that structural breaks are usually modeled on less granular data (often monthly), I attribute this change in the long-term pattern to the imminent BRC. There was also no major macroeconomic event around the break day. Duffie et al. (2017)

[30]The same test also identifies a downward structural break for the benchmark differential on 25 March 2015. Moreover, given the extreme movements in quoted spreads on days with high uncertainty and volatility, such as those when macroeconomic news announcements were made, I rerun the multiple structural breaks model using a trimmed time series in order to exclude extreme days. The break dates remain identical: 4 December 2014 and 26 March 2015. The results can be found in Figure A.4 and Figure A.5 of Appendix XI.

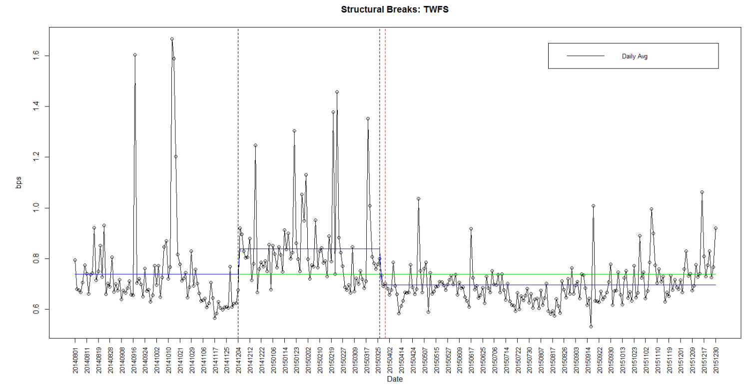
suggest that improved price transparency generated by a benchmark encourages entry by traders and stimulates dealer competition on prices, which at the same time may lead to inefficient dealers exiting the market. In addition, I argue that a more precise and regulated market-based benchmark reduces information asymmetry, positively impacting market liquidity. The fact that on 26 March 2015 the Trad-X platform experiences a 10% increase in the number of participants is in line with my argument. Figure 3.4 illustrates that the number of platform participants remains above its long-term average during the large majority of the post-BRC period.

The breaks determined for the two depth measures are different. The quoted depth time series shows three breaks: 18 December 2014, 26 March 2015, and 7 October 2015. The first and third breaks are different to the breaks established for the spread measures, but importantly the second downward break immediately precedes the BRC and suggests a slight reduction in depth at the best order book level, which is consistent with earlier findings. For the 10-level depth time series, the BP multiple structural break model identifies two breaks: 24 March 2015 and 7 October 2015. The October break is identical to the quoted depth's October break, but the March break occurs five trading days before the BRC. The fact that all liquidity measures identify a break in the long-term time series imminently prior to the transition to the ICE Swap Rate regime supports the earlier findings.

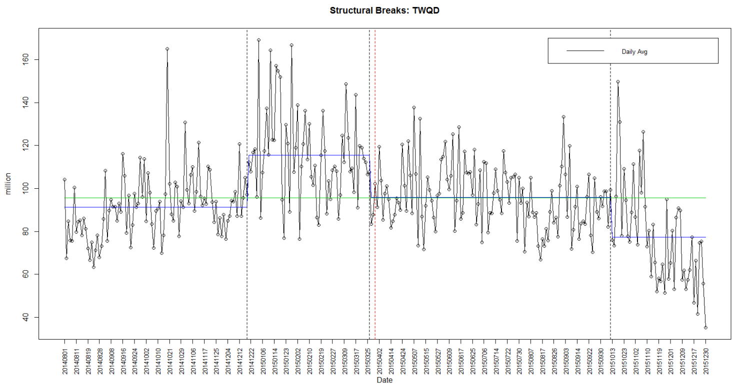
Figure 3.5. Structural breaks



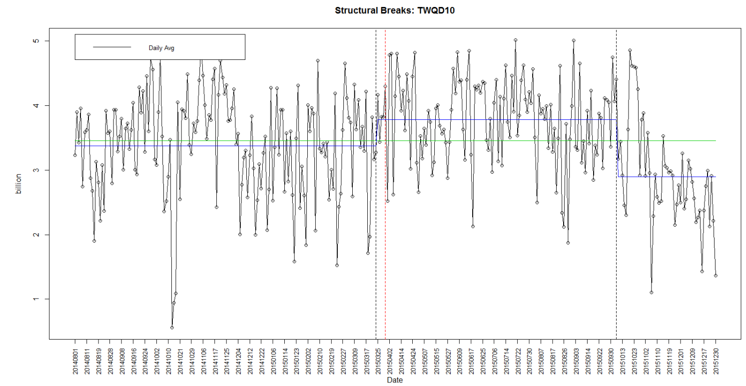
(a) Time-weighted quoted spread



(b) Time-weighted fill spread



(c) Time-weighted quoted depth



(d) Time-weighted 10-level quoted depth

Notes: This figure shows the development of the *TWQS*, *TWFS*, *TWQD*, and *TWQD10* for the 10Y USD IRS over the sample period. The black dotted lines mark the break dates as determined by the BP model. The green line depicts the long-term average of the time series, while the blue line shows the segment averages. The red dotted line marks the event date [d_0 = 31 March 2015]. *Pre-BRC* refers to the ISDAFIX regime [d_{-160} = 1 August 2014, d_{-1} = 30 March 2015]. *Post-BRC* refers to the ICE Swap Rate regime [d_0 = 31 March 2015, d_{170} = 30 December 2015]. All spread values are expressed in bps (1 bps = 0.01%) and all depth values in dollars ($).

VI. Conclusion

This study presents a model that provides a theoretical underpinning for recent regulatory interventions in financial benchmark assessments. By increasing transparency, regulatory oversight, and monitoring of the benchmark fixing process, and by reducing the probability of manipulations, such interventions cause benchmarks to send a more precise signal to the market, thus leading to better (or even optimal) market outcomes. My study complements the work of Duffie et al. (2017), who show that benchmarks can increase social surplus and have positive welfare implications.

Empirical tests of the model's predictions show that the transition on 31 March 2015 from the unregulated panel-based ISDAFIX regime to the regulated market-based ICE Swap Rate regime is linked to a measurable improvement in market liquidity. The regulatory intervention by the FCA led to an overhaul of the assessment methodology for the principal IRS benchmark, making it more transparent and tightly monitored, analogous to the noise reduction effect in the model. The liquidity improvement translates into reduced execution costs for the participants in electronically traded swaps. The cost savings for electronic transactions in the 10Y USD IRS from April 2015 to December 2015, on the Trad-X platform alone, amount to between \$4 and \$7 million. A large part of the liquidity enhancement is already captured by an increment in the number of venue participants, which coincides with the regulatory intervention—the estimate is conservative since it is impossible to attribute the beneficial impact of the concurrent increase in participation to the benchmark transition. Nonetheless, applying a DiD technique, I can attribute the liquidity enhancement to the ISDAFIX-to-ICE Swap Rate transition induced by the regulatory intervention of the FCA. Specifically, the effect is stronger for tenors with a daily benchmark determination, which are impacted directly by the change in benchmark regime, compared to tenors without reference rates. Hence, the results suggest that the influence of the regulatory regime is beyond the effect of other confounding events. I also find that the accuracy of the benchmark itself has improved following the regulatory change, with the benchmark rates now reflecting available market prices more closely.

The results of this study should be interpreted with some caution for two reasons. Firstly, I only analyze the order book data of the main inter-dealer platform, Trad-X. While Trad-X remains the principal inter-dealer platform, the contributions of the other platforms to the ICE Swap Rate benchmark assessments are not negligible. Moreover, developments in market quality on the other contributing venues and dealer-to-client platforms might look different to the observed reaction on Trad-X. However, given that these markets are traded electronically, I would expect participants to arbitrage out any meaningful differences across platforms. Secondly, this study only captures electronic trading, and is unable to account for voice broking. However, consolidating electronic and voice trading activity is not currently advisable given the inevitable timestamping issues that are bound to arise.

Overall, this study robustly demonstrates that transparent and appropriately regulated benchmarks can contribute to better financial markets. The model suggests that regulators should bear in mind that clarity for the actors taking part in the benchmark-setting process is most crucial. Thus, interventions that made the benchmark fixing process noisier would be unhelpful and likely to make traders worse off.

4

Conclusion

I. Summary

Over-the-counter (OTC) markets have long attracted academic interest. In this dissertation, my intention has been to connect search costs, transparency, and networks—three defining elements of price discovery and liquidity in decentralized markets—to benchmarks and derivatives. Benchmarks alleviate search frictions and mitigate market opacity, and derivatives promote price discovery, risk management, and transactional efficiency between different market structures.

For this purpose, the dissertation summarizes the literature on OTC markets, as well as benchmarks and derivatives, in detail in the starting Chapter 0. Each study in this thesis contributes to the ongoing debate in these literature streams. Chapter 1 focuses on the critical price discovery role of commodity benchmarks and makes a valuable addition to the growing benchmark literature, which until now has had manipulation and price patterns of related derivatives as its focal point (see for example Abrantes-Metz et al., 2012; Caminschi and Heaney, 2014; Evans, 2018; Fouquau and Spieser, 2015, and others). Chapter 2 engages with the literature on oil-spot-derivatives price discovery (see Liu et al., 2015) and the financialization of commodity markets (see Cheng and Xiong, 2014). Chapter 3 contributes to recent advancements in the academic debate on the design, reform, and regulation of financial benchmarks (see Duffie and Dworczak, 2018; Duffie et al., 2017; Duffie and Stein, 2015) and how well-designed policy interventions can enhance social welfare (see Stiglitz, 1993).

Chapter 1 documents the observed behavior of Brent futures prices and the trading patterns around the time of the physical oil benchmark assessment of Dated Brent, operated by the price reporting agency (PRA), Platts. The study is timely because the introduction of the *EU Benchmarks Regulation* will affect a wide range of commodity benchmarks. I report that the ICE Brent Crude futures are alert during the benchmark assessment from 16:00 to 16:30, as measured by significantly heightened trading volume and price volatility. Commencing with the start of the Dated Brent assessment window, the futures price begins to move in the direction of the benchmark fixing outcome, which is only published 30 minutes after that. In line with the literature on informed trading, the price experiences a reversal after the assessment ends. Based on fixing-direction-aligned order imbalances, and higher participation of informed traders in the futures market, I attribute at least part of the price adjustment to informed directional trading during the unfolding of the Dated Brent assessment period. At the same time, the Platts Window represents a period of heightened activity in the oil market, and thus also attracts many uninformed Brent futures participants, and their continued presence is critical to the transfer of price-relevant information from the physical to the financial oil market. Profit opportunities for spot-market-informed futures traders lie in the range of 8 bps to 24 bps over the full 30-minute assessment window. A likely source of information driving the directional trading is knowledge of oil supply and demand fundamentals, gained in the physical crude oil market. I further address this possibility in Chapter 2. While the robustness tests control for correlation between the developing benchmark assessment and futures price movements, and for the potential effects of confounding events, two caveats apply. The documented pattern may be magnified by herding dynamics of market participants, for example based on futures order flow signals, or the closely cointegrated relationship between the spot and futures markets that I am unable to entirely account for due to data limitations. Despite these constraints, the extensive nature of the analysis presents a consistent view that the physical oil assessment by Platts is of material importance to the price discovery of exchange-traded (ET) financial oil derivatives.

Chapter 2 investigates the often under-researched (due to data limitations) OTC forward oil market, which is inextricably linked to the frequently studied oil futures market. Creating a novel dataset, I combine intraday data from both markets, and confirm the long-standing belief that the futures market is nowadays the uncontested information leader. Using direct high-frequency observations from the physical oil market, I circumvent common data constraints and present evidence that earlier studies have been unable to provide unequivocally. Namely, I show that futures prices incorporate the majority of new information ahead of forward prices. The futures market is, by design, more active since its contracts are virtually 24-hour ET and financially settled, and therefore the findings are not surprising. Nonetheless, the forward market does contribute a non-trivial amount to oil price discovery. This is remarkable, given that forwards are characterized by proportionally few quotes and transactions, a limited number of active participants, and active trading during just five minutes at the end of the day. Besides this, the forward price is also less noisy than the futures price. This is in line with the findings of Chapter 1, suggesting that the Dated Brent assessment and the physical trading during the Platts Window substantially influence ET oil derivatives as well. In an additional element to the study, I show that forward trading reveals fundamental information, which the futures price impounds subsequently. I find support for the 'skin in the game' hypothesis, which stipulates that forward participants with close connections to the crude oil demand and supply chains possess superior information about oil fundamentals. I form a proxy for their infrastructure stakes via their network centrality in the cash BFOE market, and find that forward transactions of more central traders have a more pronounced futures price impact. The results suggest that fundamental information is a significant driver of commodity prices. Nevertheless, interpretation of the findings warrants some caution. To begin with, forwards are only actively exchanged during a couple of minutes at the end of the day, and thus detailed inferences about oil price discovery outside of this window cannot be made. Moreover, the paucity of forward data, and therefore challenges to establishing cointegration, require us to use prudence when interpreting the price discovery measures. All in all, the study confirms that the financialization of commodity markets substantially affects the way oil is traded (see Cheng and Xiong, 2014). Still, the close interrelations between futures and forward contracts ensure that both the financial and physical markets contribute to the determination of the efficient price of oil.

Chapter 3 presents a theoretical model that provides a strong rationale for many of the regulatory interventions in the benchmark space over recent years. By increasing monitoring and supervision of the benchmark fixing process, and by fostering transparency, these interventions mean that benchmarks send a more precise signal to the market, leading to better (or even optimal) market outcomes. I test this hypothesis by investigating a regulatory intervention by the Financial Conduct Authority (FCA) that reformed the principal benchmark in the OTC interest rate swap (IRS) market. The new assessment procedure is more transparent, and benefits from better controls and oversight. The transition on 31 March 2015, from the unregulated panel-based ISDAFIX regime to the regulated market-based ICE Swap Rate regime, led to a significant improvement in liquidity, reducing execution costs for market participants. The cost savings on electronic transactions in a single product traded from April 2015 to December 2015 on one platform alone, namely the 10Y USD IRS on Trad-X, amount to approximately $7 million. This is a conservative estimate, and the true number is likely larger given that part of the liquidity enhancement is attributable to the concurrent increase in the number of venue participants. Based on difference-in-difference regressions, I determine the regulatory intervention to be the driving force. The effect is stronger for swap tenors with a daily benchmark determination, which are directly affected by the regulation, than it is for tenors without a reference rate. Controlling for a wide range of other factors, the results suggest that the influence of the regulatory regime change goes beyond the effect of separate confounding events. I also find that the accuracy of the benchmark itself has improved following the regulatory change, as the benchmark rates now more closely reflect market prices. The findings need to be considered in the light of two limitations. First, market quality developments on venues other than Trad-X, the major inter-dealer swap platform, might differ from the effects reported in this study. Second, the data do not allow me to draw any conclusions about voice trading, an important element of the OTC swap market that I am unable to cover. Nevertheless, the study permits me to conclude that well-designed regulatory interventions, in this case enhancing the robustness of financial benchmarks, can contribute to better financial markets.

To summarize, each chapter makes one key contribution. Chapter 1 establishes physical commodity benchmarks as essential elements of financial market infrastructure. Chapter 2 shows that trading networks in physical commodity markets directly impact the price formation of financial derivatives. Chapter 3 demonstrates that well-designed financial regulation, that fosters transparency, can be welfare improving.

II. Discussion and implications

The implications of my findings are diverse and far-reaching.

First, Chapter 1 allows me to draw the conclusion that the definition of financial market infrastructure should not a priori be restricted to financial products, venues, and participants. The definition should include infrastructure elements from other branches of our economy, as well, that have evolved over time and nowadays occupy prominent positions in financial markets—such as commodity benchmarks. Future research should aim to reconcile OTC spot data with that on linked derivatives to further our understanding of the continuous interactions between physical and financial commodity markets. Furthermore, the EU Benchmarks Regulation will affect commodity benchmarks and their respective financial products. More research is needed to provide an understanding of the implications of extending the financial regulatory perimeter to include infrastructure elements of physical commodity markets.

Second, as demonstrated in Chapter 2, physical markets contain information that is relevant for financial derivatives markets. Trading relationships in networks might reveal activities or strategies of companies in their upstream or downstream business lines, thereby reflecting supply and demand fundamentals. I show that the OTC forward trading network reveals information that is subsequently incorporated into futures prices. Reconciling data on ET derivatives, such as futures, with that on other OTC derivatives, such as Contracts for Differences (CFDs), could lead to additional and novel insights. Further, research could focus on the behavior of trading networks around the times of commodity-sensitive announcements: do participants that are more central react in advance? Also, future studies might seek to link the physical trading activity of forwards and cargoes to regional or global supply and demand fluctuations and inventory levels. One final note relating to this project: insights can be gained by combining research methods and designs from different disciplines. Social network analysis is well-established in the social sciences, but its potential has not yet been fully realized in financial economics research.

Third, Chapter 3 underlines the importance of appropriate and balanced regulations. Well-designed regulatory interventions can positively affect the efficient functioning of financial markets and thereby enhance social welfare (see Stiglitz, 1993). Regulators should stimulate transparency and competition where markets fail to develop sufficient solutions themselves. Future research could investigate other policy actions that increased transparency and competition, and identify the effects on markets, participants, and products. Moreover, in many decentralized markets, trading takes place via parallel trading systems. Forthcoming studies should aim to consolidate data from fragmented venues and hybrid systems such as electronic order books and voice trading. I have been unable to address this challenge, but additional efforts should be made to further our understanding of trading in modern OTC markets.

III. Concluding remarks

In truly connected economies, where market structures are interacting with each other at an ever-increasing speed and to an unprecedented extent, it is essential to understand how individual elements act as crucial interfaces. Benchmarks and derivatives are such essential components. This dissertation aims to further our understanding and knowledge of the interactions between centralized and decentralized markets, through the lenses of benchmarks and derivatives. It underlines how regulation and trading networks can alter and affect the fundamental relationships between two market structures. The findings of the thesis will be of interest to market practitioners and regulators alike. ET derivatives are sensitive and alert to the assessment of physical commodity benchmarks. Moreover, trading networks in physical markets also affect information transmission and price developments of financial products. These relationships underline the role played by both physical and financial markets in the price discovery of the underlying commodities. Finally, benchmarks, in general, are integral components of the financial infrastructure, and their regulation, if well designed and executed, can improve the efficiency of markets and enhance social welfare.

A
Supplementary material

I. Platts and its Dated Brent benchmark

Platts, a division of S&P Global, is a leading information service provider for commodity markets specializing in price references and benchmarks for, amongst others, the energy market. One of its flagship benchmarks is the Dated Brent. Dated Brent is a benchmark price for physical North Sea crude oil. *Dated* refers to a physical cargo of North Sea Brent-Forties-Oseberg-Ekofisk (BFOE) crude oil that has been assigned a loading date for shipping (has become wet) no less than 10 days forward.

The assessment of Dated Brent started in 1980. In July 2002, Platts launched a process called Market on Close (MOC)[1] to assess the daily price of Dated Brent, and due to declining production of Brent added two grades to its assessment: Forties and Oseberg. The loading date range of cargoes considered in the assessment was also widened, to 10–21 days forward. In June 2007, Ekofisk was added to the basket. On 6 January 2012, Platts widened the date range again, to 10–25 days forward. Finally, in 2015, the date range was extended to 10–30 days forward.

A central element of the MOC is the 30-minute time frame, from 16:00 to 16:30 London local time, called the *Window*. Platts operates an online data-entry and communications system called *eWindow* (Platts Editorial Window), which is an over-the-counter (OTC) real-time open order book revealing transaction data and bids and offers communicated to Platts by the market participants. The eWindow tool facilitates price discovery in the physical oil market, as it is compatible with the *WebICE* trading platform of the Intercontinental Exchange (ICE), designed to combine state-of-the-art trading technology with the functionalities required for trading in the OTC market.

Platts determines the Dated Brent price based on a combination of data received for three OTC variables: (i) physical North Sea cargoes, (ii) short-term swaps between

[1]The MOC process has the advantage of reflecting market conditions more precisely at the end of the day than an averaging approach, and takes structure (contango/backwardation) into account.

Dated Brent and Forward Brent (i.e., Contracts for Differences, CFDs), and (iii) outright Forward Brent (also called cash BFOE). In order to become a so-called *market maker* in the Platts Window, a participant must indicate his interest in trading to Platts ahead of a certain cut-off period, by submitting a new bid/offer. After the cut-off period, no new bids/offers are accepted, and only existing quotes can be amended. However, so-called *market takers* can hit the bid or lift the offer of a market maker at any time. The window itself can thereby be divided into three phases. The cut-off times for new bids/offers are 16:10:00 for physical North Sea cargoes, 16:15:00 for CFDs, and 16:25:00 for cash BFOE, and thereafter only existing quotes can be amended.[2] Physical North Sea bids/offers can be changed until 16:25:00. Quotes for CFD bids/offers can also be amended until 16:25:00. Finally, bids/offers for cash BFOE can be changed until the close at 16:30:00. Price changes need to be incremental (under normal market conditions up to 5 ¢/barrel) and prices must stand firm long enough to be acted upon by a counterparty, in order to ensure orderly price discovery. After 16:30:00 all bids/offers that have not been acted upon during the Platts Window expire.[3] Platts' editorial team takes all the data collected during the 30-minute period and calculates the Dated Brent Strip based on the quoting and trading activity of the aforementioned variables. A price is then established for each of the four North Sea oil grades (Brent, Forties, Oseberg, Ekofisk), with the most competitive grade setting the daily Dated Brent price. The Dated Brent reflects the spot market value of the most competitive BFOE grade at 16:30 London time.

A key requirement for participating in the Dated Brent assessment is following Platts' rules and guidelines, designed to ensure the transparency, integrity, and reliability of the benchmark. Platts pays particular attention to the repeatability of transactions, such that traders do not engage in non-repeatable transactions to bias the market's perception

[2]Source: http://www.rusneftekhim.com/docs/crude_oil.pdf.

[3]Information received during the *Platts Oil Methodology Explained* session at the *Platts London Oil & Energy Forum.*

of the true value. Moreover, prices need to evolve sequentially and incrementally, and Platts does not consider quotes that are the result of price gapping.

It is important to note that the window is merely a part of the whole MOC price-setting process, and Platts monitors the physical market throughout the trading day as well. The MOC methodology has the advantage of promoting liquidity, in a rather illiquid market, as it leads to a natural concentration of activity in a short period at the end of the day (Barret, 2012a). Typically, the window, therefore, experiences the highest participant activity. Although the OTC physical oil market is effectively open 24 hours, the price at 16:30 London time reflects the most useful price for the day at the 'close' of the physical market.

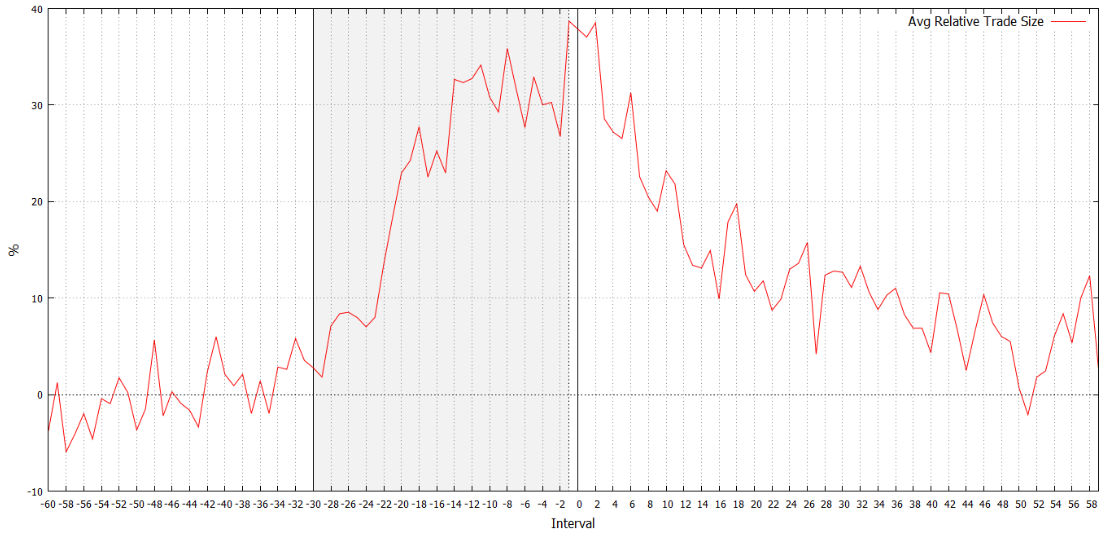
The minimum trade size for physical BFOE is a partial cargo of 100,000 barrels, and a full cargo corresponds to 600,000 barrels. The minimum shipment size acts as barrier-to-entry to the physical oil market such that, typically, during the Platts Window only a handful of participants contribute to the price assessment at any given time, and of those even fewer account for roughly half of the total trading activity (Barret, 2012a; Fattouh, 2011). The participating companies are mostly major oil multinationals or large commodity traders, but also include financial institutions. Companies wishing to participate in the Platts Dated Brent assessment need to pass Platts' vetting and due diligence process, which consists, amongst other things, of checks on the credibility, creditworthiness, ownership structure, logistical ability, trade performance history, and market acceptance by counterparties of the applicant.[4]

[4]Information given in this appendix was received at the *Platts Oil Methodology Explained* session hosted by Platts in London. For more information and references on the MOC price assessment methodology see http://www.rusneftekhim.com/docs/crude_oil.pdf, http://www.platts.com/products/ewindow, and https://www.platts.com/IM.Platts.Content/aboutplatts/mediacenter/PDF/intromocoil.pdf.

II. Relative trade size evolution around the Dated Brent benchmark assessment

Trade size in interval t is defined as the division of the trading volume by the number of trades. For the computation of the average relative trade size, $\overline{TS}_t$, I follow the same rationale as described in Equations 1.1 and 1.2. Figure A.1 shows that $\overline{TS}_t$ gradually increases during the 30-minute Platts Window, up to a maximum of nearly 40% above the reference level, and reverts to its previous levels after the end of the price fixing. The reversion in trade size, however, is moderate compared to that for the volume and volatility measures. The larger trade sizes suggest a degree of urgency in trade completion, consistent with trading behavior associated with short-lived information.

Figure A.1. Average relative trade size



Notes: Figure A.1 shows the average relative trade size. The measure is reported in percentage terms (%). The shaded area indicates the event window from fixing start (t_{-30}) to fixing end (t_{-1}) [16:00:00, 16:29:59]. The vertical black line marks the interval following the Platts Dated Brent assessment end: t_0 [16:30:00, 16:30:59].

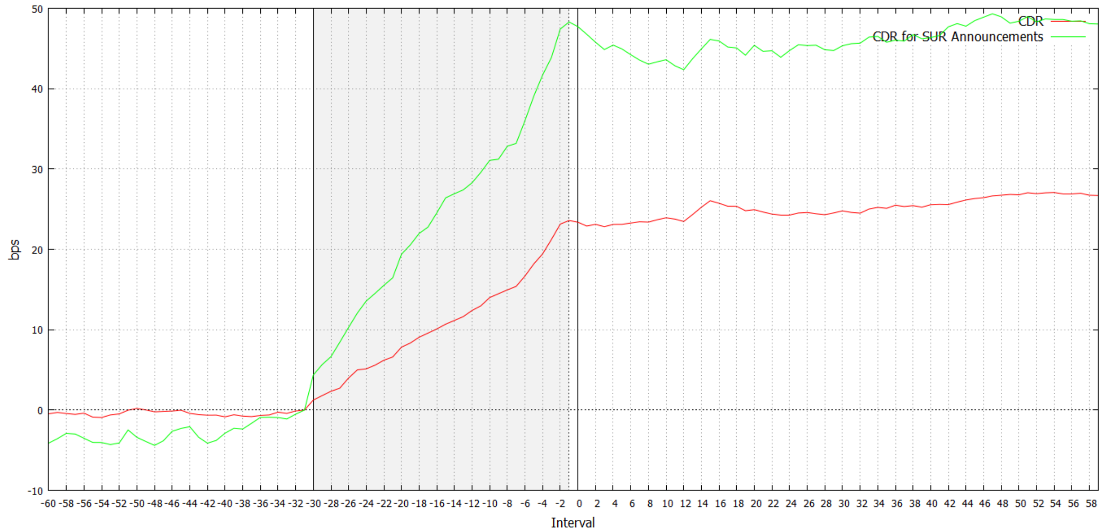
III. Surprise announcements and sentiment differences

The *SUR* dummy in Panel A of Table 1.6 implies that *DR* is, on average, higher on days with a surprise announcement (1% significance level). Theoretically, the profit potential of directional traders is greater on days with surprise announcements. Figure A.2 shows that surprise Dated Brent price announcements more than double the average daily potential gain to an average of nearly 48 bps over the 30-minute assessment window, compared to an average of roughly 24 bps for all sample days. This is also consistent with the insights gained from the co-movement analysis presented in Sub-section IV.E. Furthermore, the interval-by-interval *DOIB$* during the benchmark assessment are, on average, several percentage points higher on surprise announcement days (see Figure A.3). Directional traders are even more likely to trade in the direction of the ongoing benchmark fixing on surprise announcement days; that is, the imbalance between fixing-direction-aligned transactions and transactions in the opposite direction is more pronounced.[5]

The negative and highly statistically significant *SENT* dummy variable coefficient seen in Panel A of Table 1.6 suggests that, over the full window of investigation [15:30, 17:29], the directional futures returns on days with a positive Dated Brent fixing direction do behave differently compared with days with a negative fixing direction. Similarly, the negative and statistically significant *SENT* coefficient in Panel B of Table 1.6 implies that interval-by-interval order imbalance during the benchmark assessment is more pronounced on negative fixing days. This is consistent with the generally accepted phenomenon of a stronger market reaction to negative news. The cumulative directional returns observed in Panel A of Figure 1.3 of the main paper show that the profit po-

[5]Statistical tests support the results illustrated in this figure. For parsimony, the statistical tables are not presented, but are available on request.

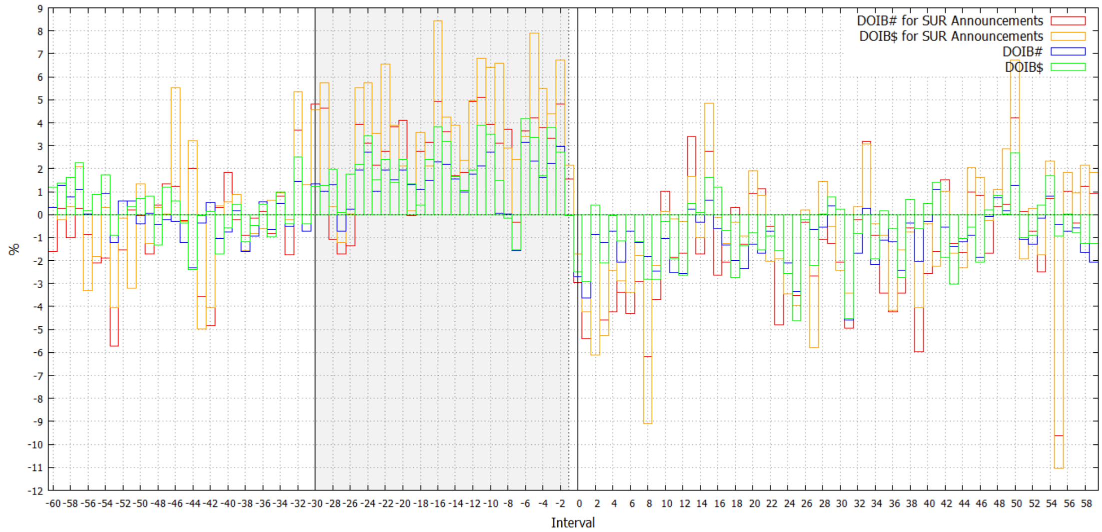
Figure A.2. Cumulative directional returns for surprise announcements



Notes: Figure A.2 shows the CDR for days with surprise Dated Brent announcements (SUR = 1) versus all announcement days. All return measures are reported in bps (1 bps = 0.01%). The shaded area indicates the event window from fixing start (t_{-30}) to fixing end (t_{-1}) [16:00:00, 16:29:59]. The vertical black line marks the interval following the Platts Dated Brent assessment end: t_0 [16:30:00, 16:30:59].

tential on negative sentiment days is approximately 31 bps, while it is only 17 bps on positive sentiment days. Furthermore, in the post-event window, negative fixing days are characterized by a more pronounced price reversal of several bps, whereas positive fixing days experience a drift ex-post of the announcement.

Figure A.3. *DOIB#* and *DOIB$* for surprise announcements



Notes: Figure A.3 shows the *DOIB#* (by number of trades) and *DOIB$* (dollar value) for days with surprise Dated Brent announcements (SUR = 1) versus all announcement days. All order imbalance measures are reported in percentage terms (%). The shaded area indicates the event window from fixing start (t_{-30}) to fixing end (t_{-1}) [16:00:00, 16:29:59]. The vertical black line marks the interval following the Platts Dated Brent assessment end: t_0 [16:30:00, 16:30:59].

IV. Data filters

For the price discovery analysis:

- I only include the forward front-month and the respective futures front-month activity.
- I exclude observations where bid > ask and where either the bid, ask, or last trade price equals zero and omit forward quotes that are more than four standard deviations away from the daily mean.
- I exclude days where I am unable to compute a forward mid-price because either bid or ask quotes are unavailable over the whole trading day.
- I only include forward trading from 16:22:00 to 16:30:00 (on normal Platts Dated Brent assessment days) and 12:22:00 to 12:30:00 (on early Platts Dated Brent assessment days) respectively. The reason is that, due to the functioning of the Platts eWindow, 99% of the activity takes place in this time window at the end of each trading day. The early assessment days are 2012-04-05, 2012-12-24, 2012-12-31, 2013-03-28, 2013-12-24, 2013-12-31, 2014-04-17, 2014-12-24, 2014-12-31, 2015-04-02, 2015-12-24, 2015-12-31, 2016-03-24, 2016-12-23, 2016-12-30, 2017-04-13, 2017-12-22, and 2017-12-29.
- On each trading day, for the calculation of the price discovery metrics, I define the first timestamp to be the time $t_1 = 1$ of the first forward quote ($n = 1$). The last timestamp corresponds to the time 60 seconds after the last forward quote on that day ($n = N$), $t_N = T + 60$, where $n = 1, ..., N$ and $t = 1, ..., T$. I thus do a full join of futures and forward data within the time range $[t_1 = 1; t_N = T + 60]$. I do this to allow for a potential adjustment of the futures price to the last forward quote. Doing this, I also avoid using a standardized time window and thereby biasing the results by including many stale forward quotes. For example, on one

day the last forward quote might be received at 16:27:35, while on the next day the last forward quote might only arrive at 16:29:58. If I were to sample on a fixed window, I would, in the first case, include a vast number of futures quotes up to 16:30:00, after price discovery in the forward market had already stopped, and the forward quote would be stale for more than two minutes.

- I remove all days on which the variation in the forward quotes is below the first percentile level of the quote variation on all days. I need a minimum quote variation in the forward market to establish cointegration.
- I remove days on which the forward and futures contracts are not cointegrated at the 75% confidence level or higher. I use the Akaike information criterion (AIC) test to determine the optimal number of lags, allowing for a maximum of 60 lags.

For the price impact analysis:

- I only include the forward front-month and the respective futures front-month activity.
- I exclude observations where bid > ask and where either the bid, ask, or last trade price equals zero and exclude forward quotes that are more than four standard deviations away from the daily mean.
- I only include front-month forward transactions, all of which were executed between 16:25:00 and 16:30:00 (on normal Platts Dated Brent assessment days) and 12:25:00 and 12:30:00 (on early Platts Dated Brent assessment days) respectively.
- I compute the price impact measures on the futures price over a 10-minute window, using $+-$five minutes to determine the pre- and post-benchmark prices. The results are robust to choosing $+-10$ minutes or $+-15$ minutes instead. I do not use less than five minutes because, for a robust calculation of the price impact, the pre- and post-benchmark prices should fall outside the 16:25:00–16:30:00 period

of the Platts Dated Brent assessment.

V. Control variables

- *CENT* is the ECDF-normalized weighted out-degree measure of each forward trader, ranging from 0 = least central to 1 = most central, calculated from the network presented in Section IV.B. The network and centrality are determined based on all forward transactions in all contract months over the full sample period. The reason for using the full sample period is that I aim to measure the importance of a market maker, and its reputation as a major trading participant, established over time. I use transactions in all contract months to capture the overall standing of a trader in the market, even though I only measure the front-month price impact.
- *log(VOL)* is the log futures volume over the price impact assessment window.
- *log(VOLA)* is the standard deviation of futures log returns over the price impact assessment window.
- *QBUY* is the forward buy volume in the front-month contract by trading day.
- *QSELL* is the forward sell volume in the front-month contract by trading day.
- *log(PM)* is the log return between the forward transaction price at time t, and the first quote price of the related order ahead of execution. This variable accounts for potential price adjustments in the forward market in the direction of the upcoming trade, ahead of its completion.
- *OILM* is a dummy that takes the value 1 for companies that are oil majors and 0 otherwise.
- *OILT* is a dummy that takes the value 1 for companies that are commodity trading houses and 0 otherwise.

- *log(HHI)* is the log Herfindahl-Hirschman Index by forward contract month, where the market share for each trader and contract month is determined by the gross notional of the forwards transacted. This variable approximates and controls for market concentration and competition.
- *BMCHG* takes the value 1 after 2015-02-01 to control for the potential effect of Platts changing the Dated Brent assessment period to 10-30 days ahead. This had an impact on the expiry of BFOE forwards too.
- *FUTCHG* takes the value 1 after 2016-02-01 to control for the potential effect of changes to the futures contract expiry, extending it to a two-months-ahead contract and thereby aligning it with the forward contract.
- *WEEKD()* are dummies accounting for day-of-the-week effects. The baseline category is Monday.

VI. Price impact regressions: Without controls

Table A.1. Price impact of forward trades on futures market: Without controls

	Dependent variable:					
	PE		TE		LE	
	Buy	Sell	Buy	Sell	Buy	Sell
CENT	0.12*** (0.03)	−0.12*** (0.04)	0.16*** (0.05)	−0.16*** (0.03)	0.04 (0.04)	−0.03 (0.02)
Constant	−0.08*** (0.03)	0.05** (0.03)	−0.12*** (0.04)	0.07*** (0.02)	−0.04 (0.03)	0.02 (0.02)
Observations	2,083	2,473	2,083	2,473	2,083	2,473
R^2	0.01	0.01	0.02	0.02	0.00	0.00
Adjusted R^2	0.01	0.01	0.02	0.02	0.00	0.00
Residual Std. Error	0.28 (df = 2081)	0.27 (df = 2471)	0.22 (df = 2081)	0.24 (df = 2471)	0.18 (df = 2081)	0.18 (df = 2471)

Notes: *p<0.1; **p<0.05; ***p<0.01. *CENT* measures the centrality of the forward market participants in terms of the ECDF-normalized weighted out-degree [0 = least central; 1 = most central]. Please refer to Appendix V for a detailed explanation of the control variables. The coefficients are reported in percentage terms (%). Robust standard errors clustered at the trader level are reported in parentheses.

VII. Correlation matrix

Table A.2. Correlation matrix of control variables

	CENT	log(VOL)	log(VOLA)	QBUY	QSELL	log(PM)	OILM	OILT	log(HHI)	BMCHG	FUTCHG	MON	TUE	WED	THU	FRI
CENT	1	-0.03	-0.07	-0.00	-0.04	0.05	0.43	-0.08	0.16	-0.13	-0.18	-0.00	-0.02	-0.02	0.02	0.02
log(VOL)	-0.03	1	0.31	-0.05	0.04	-0.01	-0.03	0.03	-0.07	0.17	0.20	-0.04	0.05	0.04	-0.09	0.03
log(VOLA)	-0.07	0.31	1	-0.09	0.21	-0.11	-0.12	0.12	-0.34	0.69	0.38	-0.04	0.02	0.08	-0.03	-0.04
QBUY	-0.00	-0.05	-0.09	1	-0.27	0.26	0.03	-0.01	0.04	-0.11	-0.02	0.02	-0.06	0.06	0.03	-0.05
QSELL	-0.04	0.04	0.21	-0.27	1	-0.26	-0.11	0.08	-0.14	0.16	-0.02	0.01	0.07	0.03	-0.02	-0.09
log(PM)	0.05	-0.01	-0.11	0.26	-0.26	1	0.06	-0.05	0.06	-0.09	0.04	-0.00	-0.00	-0.00	0.00	0.01
OILM	0.43	-0.03	-0.12	0.03	-0.11	0.06	1	-0.76	0.16	-0.12	-0.12	-0.02	0.01	-0.02	0.00	0.04
OILT	-0.08	0.03	0.12	-0.01	0.08	-0.05	-0.76	1	-0.13	0.14	0.09	0.03	-0.04	0.02	0.03	-0.04
log(HHI)	0.16	-0.07	-0.34	0.04	-0.14	0.06	0.16	-0.13	1	-0.41	-0.16	0.00	-0.01	0.02	-0.02	0.01
BMCHG	-0.13	0.17	0.69	-0.11	0.16	-0.09	-0.12	0.14	-0.41	1	0.56	-0.02	0.04	-0.01	0.02	-0.04
FUTCHG	-0.18	0.20	0.38	-0.02	-0.02	0.04	-0.12	0.09	-0.16	0.56	1	-0.00	0.02	-0.00	0.02	-0.03
MON	-0.00	-0.04	-0.04	0.02	0.01	-0.00	-0.02	0.03	0.00	-0.02	-0.00	1	-0.27	-0.26	-0.25	-0.23
TUE	-0.02	0.05	0.02	-0.06	0.07	-0.00	0.01	-0.04	-0.01	0.04	0.02	-0.27	1	-0.27	-0.26	-0.24
WED	-0.02	0.04	0.08	0.06	0.03	-0.00	-0.02	0.02	0.02	-0.01	-0.00	-0.26	-0.27	1	-0.25	-0.24
THU	0.02	-0.09	-0.03	0.03	-0.02	0.00	0.00	0.03	-0.02	0.02	0.02	-0.25	-0.26	-0.25	1	-0.22
FRI	0.02	0.03	-0.04	-0.05	-0.09	0.01	0.04	-0.04	0.01	-0.04	-0.03	-0.23	-0.24	-0.24	-0.22	1

Notes: This table reports the Pearson correlation of the regression control variables. Please refer to Appendix V for a detailed explanation of the control variables.

VIII. Additional results: Yearly compounded centrality

Table A.3. Price impact of forward trades: Yearly compounded centrality

	Dependent variable:					
	PE		TE		LE	
	Buy	Sell	Buy	Sell	Buy	Sell
CENT	0.10*** (0.03)	−0.08** (0.03)	0.12*** (0.05)	−0.12*** (0.03)	0.02 (0.03)	−0.04** (0.02)
log(VOL)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	−0.01 (0.01)	−0.01 (0.01)	−0.01** (0.01)
log(VOLA)	−0.08** (0.03)	−0.04** (0.02)	−0.08*** (0.02)	−0.06*** (0.02)	−0.00 (0.02)	−0.02 (0.02)
QBUY	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)	0.00 (0.00)	−0.00 (0.00)	−0.00*** (0.00)
QSELL	−0.00 (0.00)	−0.00*** (0.00)	−0.00** (0.00)	−0.00*** (0.00)	−0.00 (0.00)	0.00 (0.00)
log(PM)	14.38*** (2.02)	11.85*** (1.39)	15.04*** (1.23)	12.46*** (1.33)	0.66 (1.41)	0.60 (0.55)
OILM	0.02 (0.02)	0.02 (0.02)	0.00 (0.02)	−0.00 (0.02)	−0.02 (0.02)	−0.02 (0.02)
OILT	0.02 (0.02)	0.01 (0.02)	−0.00 (0.02)	0.00 (0.02)	−0.03 (0.02)	−0.01 (0.01)
log(HHI)	−0.10*** (0.02)	−0.08*** (0.02)	−0.03*** (0.01)	−0.02 (0.03)	0.06*** (0.01)	0.05*** (0.02)
BMCHG	−0.00 (0.05)	0.00 (0.02)	0.00 (0.03)	0.04* (0.02)	0.00 (0.02)	0.03** (0.01)
FUTCHG	0.05 (0.04)	−0.02 (0.03)	0.04* (0.03)	−0.01 (0.03)	−0.01 (0.03)	0.02 (0.01)
WEEKD(TUE)	0.03 (0.03)	0.01 (0.02)	0.01 (0.02)	0.01 (0.02)	−0.02 (0.02)	0.01 (0.01)
WEEKD(WED)	−0.06*** (0.02)	0.00 (0.02)	−0.04*** (0.01)	−0.01 (0.02)	0.02 (0.01)	−0.01 (0.02)
WEEKD(THU)	−0.02 (0.03)	−0.00 (0.02)	−0.03 (0.02)	−0.00 (0.02)	−0.00 (0.02)	0.00 (0.01)
WEEKD(FRI)	−0.02 (0.03)	−0.04** (0.02)	−0.00 (0.02)	−0.00 (0.02)	0.02 (0.02)	0.04** (0.02)
Constant	−1.13*** (0.36)	−0.45** (0.19)	−0.99*** (0.22)	−0.34 (0.23)	0.15 (0.19)	0.11 (0.16)
Observations	2,083	2,473	2,083	2,473	2,083	2,473
R^2	0.09	0.10	0.14	0.12	0.03	0.04
Adjusted R^2	0.08	0.10	0.13	0.11	0.02	0.04
Residual Std. Error	0.27 (df = 2067)	0.26 (df = 2457)	0.21 (df = 2067)	0.22 (df = 2457)	0.18 (df = 2067)	0.17 (df = 2457)

Notes: *p<0.1; **p<0.05; ***p<0.01. *CENT* measures the yearly compounded trader centrality in terms of ECDF-normalized weighted out-degree [0 = least central; 1 = most central] and is computed starting with all trades from 2012-2013, then from 2012-2014, etc., until we incorporate all trades from 2012-2017. This allows us to account for changes in ranking over time and additions and withdrawals of participants. The coefficients are reported in percentage terms (%). Robust standard errors clustered at the trader level are reported in parentheses.

IX. Data disclaimer

The following legal disclaimer applies to the data supplied by Tradition:

X. Carlson and McAfee (1983) proof

First, the expected gain from searching for a price lower than p_i and the expected demand q_i can be written as

$$\sum_{k=1}^{i-1}(p_i - p_k)Pr(p_k) \equiv \frac{1}{n}\left[(i-1)p_i - \sum_{k=1}^{i-1} p_k\right] \tag{A.1}$$

$$q_i = \sum_{k=i}^{n} \frac{1}{k}\left[G(x_{k+1}) - G(x_k)\right] \equiv \frac{1}{n}G(x_{n+1}) - \frac{1}{i}G(x_i) + \sum_{k=i+1}^{n} \frac{1}{k(k-1)}G(x_k) \tag{A.2}$$

Second, by induction, the following equivalence holds:

$$\sum_{k=i+1}^{n} \frac{1}{k(k-1)} = \frac{n-i}{ni} \tag{A.3}$$

Then, from (A.2) and the cost distribution (3.2),

$$q_i = \frac{v - p^*}{sn} - \frac{x_i}{si} + \sum_{k=i+1}^{n} \frac{x_k}{sk(k-1)}$$

In equilibrium, the search cost equals the expected gain from searching for a lower price.

Using (A.1), the following is obtained:

$$
\begin{aligned}
q_i =& \frac{1}{sn}\left\{v - p^* - \frac{\left[(i-1)p_i - \sum_{j=1}^{i-1} p_j\right]}{i} + \sum_{k=i+1}^{n} \frac{\left[(k-1)p_k - \sum_{j=1}^{k-1} p_j\right]}{k(k-1)}\right\} \\
=& \frac{1}{sn}\left\{v - p^* - p_i + \frac{1}{i}p_i + \frac{\sum_{j=1}^{i-1} p_j}{i} + \sum_{k=i+1}^{n} \frac{p_k}{k} - \sum_{k=i+1}^{n}\sum_{j=1}^{k-1} \frac{p_j}{k(k-1)}\right\} \\
=& \frac{1}{sn}\left\{v - p^* - p_i + \frac{\sum_{j=1}^{i} p_j}{i} + \sum_{k=i+1}^{n} \frac{p_k}{k} - \sum_{k=i+1}^{n}\sum_{j=1}^{k-1} \frac{n-i}{ni}p_j\right\} \\
=& \frac{1}{sn}\left\{v - p^* - p_i + \frac{\sum_{j=1}^{i} p_j}{i} + \sum_{k=i+1}^{n} \frac{p_k}{k} - \sum_{k=i+1}^{n}\sum_{j=1}^{k-1} \frac{p_j}{i} + \sum_{k=i+1}^{n}\sum_{j=1}^{k-1} \frac{p_j}{n}\right\} \\
=& \frac{1}{sn}\left\{v - p^* - p_i + \sum_{j=1}^{n} \frac{p_j}{n}\right\} \\
=& \frac{1}{sn}\left\{v - p^* - p_i + p^*\right\} \\
=& \frac{v - p_i}{sn}
\end{aligned}
$$

Derivation of Δ

Dealers set the price p_i to minimize the penalty Δ. From the quantity equation (3.4) and the price equation (3.6),

$$
q_i = \frac{v - a_i - \Delta F\left(\bar{y} - \frac{\sum_i a_i}{n}\right)}{sn}
$$

is obtained. Dealers know traders expect $p_i = a_i$ and arranging the previous equation leads to the following:

$$
\Delta = \frac{v - p_i - snq_i}{F\left(\bar{y} - \frac{\sum_i p_i}{n}\right)} \tag{A.4}
$$

So, each dealer i solves

$$
\min_{p_i} \Delta
$$

From the first-order conditions, it follows that

$$-1 + \frac{v - p_i - snq_i}{F\left(\bar{y} - \frac{\sum_i p_i}{n}\right)} \frac{f\left(\bar{y} - \frac{\sum_i p_i}{n}\right)}{n} = 0$$

and using (A.4), the outcome is

$$\Delta = \frac{n}{f\left(\bar{y} - \frac{\sum_i p_i}{n}\right)}$$

Derivation of p_i

Traders maximize their utility

$$\max_{\bar{y}} v - p_i(a_i, \bar{y})$$

Using the price equation (3.6), and from the first-order conditions,

$$n\left[1 - \frac{F\left(\bar{y} - \frac{\sum_i a_i}{n}\right) f'\left(\bar{y} - \frac{\sum_i a_i}{n}\right)}{f^2\left(\bar{y} - \frac{\sum_i a_i}{n}\right)}\right] = 0$$

is obtained, from which

$$F\left(\bar{y} - \frac{\sum_i a_i}{n}\right) = \frac{f^2\left(\bar{y} - \frac{\sum_i a_i}{n}\right)}{f'\left(\bar{y} - \frac{\sum_i a_i}{n}\right)}$$

Using this result, the price equation (3.7) becomes

$$p_i = a_i + n\frac{f\left(\bar{y} - \frac{\sum_i a_i}{n}\right)}{f'\left(\bar{y} - \frac{\sum_i a_i}{n}\right)} \tag{A.5}$$

To clearly state the role of precision in the benchmark fixing, define $\zeta \equiv \frac{\bar{y}-\frac{\sum_i a_i}{n}}{\sigma}$, and let $h(\zeta)$ be ζ's density function. Then, by changing the variable in (A.5), p_i equals

$$p_i = a_i + n\sigma \frac{h(\zeta)}{h'(\zeta)}$$

The model without scaling

To avoid scaling the support of the distribution in Equation 3.2, it is assumed that the benchmark affects each dealer with a different probability of being punished. Without scaling the distribution, $G(x)$ equals

$$G(x) = \begin{cases} \frac{x}{s} & \text{if } 0 \leq x \leq v \\ \frac{v}{s} & \text{if } x > v \end{cases} \tag{A.6}$$

From Appendix X, this distribution would lead to

$$q_i = \frac{v + p^* - p_i}{sn}$$

with different probabilities for each dealer i:

$$p_i = a_i + n \frac{F_i\left(\bar{y} - \frac{\sum_j a_j}{n}\right)}{f_i\left(\bar{y} - \frac{\sum_j a_j}{n}\right)}$$

Then,

$$q_i = \frac{v + \frac{\sum_{k=1}^n a_k}{n} - a_i + n\left[\sum_{k=1}^n \frac{F_k\left(\bar{y}-\frac{\sum_j a_j}{n}\right)}{nf_k\left(\bar{y}-\frac{\sum_j a_j}{n}\right)} - \frac{F_i\left(\bar{y}-\frac{\sum_j a_j}{n}\right)}{f_i\left(\bar{y}-\frac{\sum_j a_j}{n}\right)}\right]}{sn}$$

By following the steps as in Appendix X,

$$q_i = \frac{v + \frac{\sum_{k=1}^{n} a_k}{n} - a_i + n\left[\sum_{k=1}^{n} \frac{\sigma_k}{n} \frac{h_k(\zeta_k)}{h'_k(\zeta_k)} - \sigma_i \frac{h_i(\zeta_i)}{h'_i(\zeta_i)}\right]}{sn}$$

where $\zeta_i \equiv \frac{\bar{y} - \frac{\sum_i a_i}{n}}{\sigma_i}$.

When the distribution is not scaled, the effects of marginal costs and noise on the expected demand are with respect to the average marginal cost and noise in the market. There are also inefficiencies in this case: an efficient dealer ($\frac{\sum_{k=1}^{n} a_k}{n} > a_i$) may have a low demand just because noise affects him more than the market average ($\sum_{k=1}^{n} \frac{\sigma_k}{n} \frac{h_k(\zeta_k)}{h'_k(\zeta_k)} < \sigma_i \frac{h_i(\zeta_i)}{h'_i(\zeta_i)}$). As in the case with the scaled distribution, an increase in precision moves the outcome closer to the first best which, in this case, is $p_i = a_i$ and $q_i = \frac{v + \frac{\sum_{k=1}^{n} a_k}{n} - a_i}{sn}$.

The model without penalty Δ

If no penalty Δ is available, then each dealer i will choose his price p_i to maximize the profits, given the expected demand (while in the penalty case he chooses p_i to minimize Δ), i.e.,

$$\max_{p_i} p_i q_i - a_i q_i$$

Using Equation 3.4,

$$\max_{p_i} (p_i - a_i) \frac{v - p_i}{sn}$$

From the first-order conditions,

$$p_i = \frac{v + a_i}{2}$$

Therefore, Δ is needed to map the noise in the benchmark fixing into the prices. Also, in the case where the penalty Δ is available, the price equation is

$$p_i = a_i + n\sigma \frac{h(\zeta)}{h'(\zeta)}$$

Then, traders have an incentive to punish the dealers if the price with Δ is lower than the price without it:

$$\frac{v + a_i}{2} > a_i + n\sigma \frac{h(\zeta)}{h'(\zeta)}$$

from which

$$v > a_i + 2n\sigma \frac{h(\zeta)}{h'(\zeta)}$$

Therefore, the implicit assumption is that traders highly value the good they are trading.

XI. Additional results: ICE Swap Rate

Table A.4. Execution costs under the ISDAFIX and ICE Swap Rate regimes

	Fill spreads			
	TWFS2	*TWFS3*	*TWFS4*	*TWFS5*
Mean				
Pre	0.88	0.95	1.00	1.04
Post	0.78	0.85	0.91	0.95
t-Stat	-4.96***	-4.62***	-4.65***	-4.75***
%-Diff	-10.92%	-10.71%	-9.75%	-8.70%
Median				
Pre	0.82	0.89	0.95	1.00
Post	0.76	0.82	0.88	0.93
t-Stat	-5.21***	-4.82***	-4.5***	-4.3***
%-Diff	-7.97%	-7.96%	-7.80%	-7.60%
Std Dev				
Pre	0.18	0.20	0.20	0.20
Post	0.12	0.13	0.13	0.12
t-Stat	-2.88***	-2.75***	-3.02***	-3.32***
%-Diff	-33.45%	-32.95%	-34.91%	-36.53%

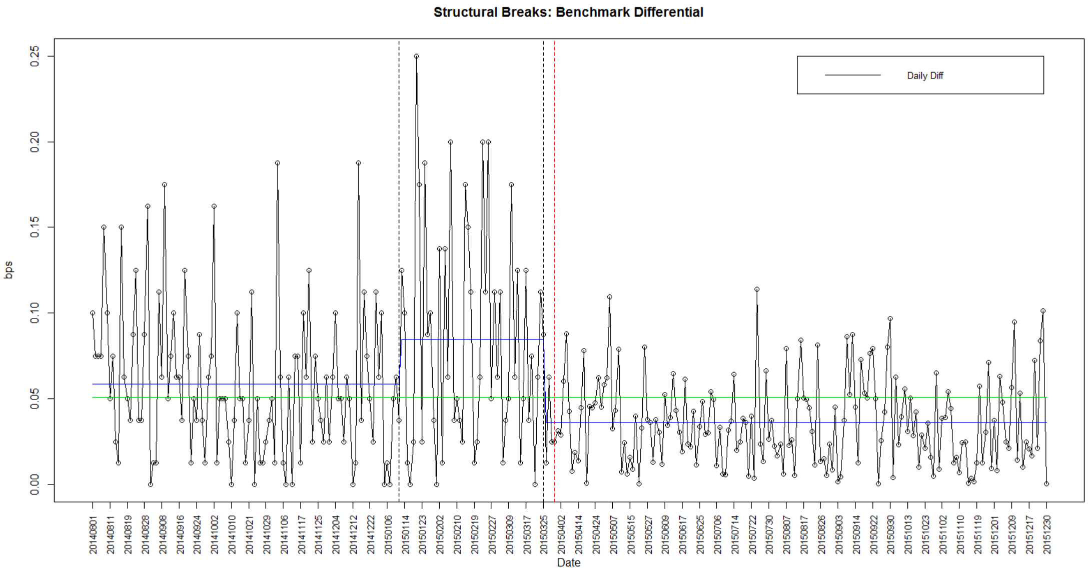
Notes: This table reports the long-term comparison of the *TWFS* for large transactions in the 10Y tenor before and after the BRC, by simulating the execution of a large transaction of some multiple of the SMS. The multiple for *TWFS2*, *TWFS3*, *TWFS4*, and *TWFS5* is 2x, 3x, 4x, and 5x the SMS respectively. The liquidity measures are computed as daily averages (medians) and then averaged across the period of interest. The median captures the weighted median (by number of occurrences) of the liquidity measures. Standard deviation reports the average daily standard deviation of the liquidity measures. *Pre-BRC* refers to the ISDAFIX regime [d_{-160} = 1 August 2014, d_{-1} = 30 March 2015]. *Post-BRC* refers to the ICE Swap Rate regime [d_0 = 31 March 2015, d_{170} = 30 December 2015]. All spread measures are expressed in bps (1 bps = 0.01%). The t-value is the statistic of a two-sample t-test of $\mu_1 - \mu_2 = 0$. *, **, and *** correspond to statistical significance at 10%, 5%, and 1% levels respectively. *%-Diff* reports the simple percentage difference between the two periods.

Table A.5. Difference-in-difference panel regressions for depth measures

	TWQD				*TWQD10*			
	(1)		*(2)*		*(1)*		*(2)*	
	Coeff	*t-Stat*	*Coeff*	*t-Stat*	*Coeff*	*t-Stat*	*Coeff*	*t-Stat*
Constant	8.33E+07	51.08***	2.10E+07	0.48	1.38E+09	33.55***	-7.73E+09	-6.98***
Event	-5.71E+06	-2.37**	-1.05E+07	-3.45***	-1.46E+07	-0.2	-3.28E+08	-4.16***
Treatment	1.75E+07	9.16***	1.74E+07	8.98***	2.01E+09	38.97***	2.01E+09	38.43***
Interaction	-4.54E+06	-1.4	-3.71E+06	-1.18	1.48E+08	2.15**	1.54E+08	2.21**
SRVIX			9.81E+07	0.6			-1.20E+09	-0.5
TYVIX			-2.41E+07	-1.16			-6.62E+08	-1.27
MESS_10Y			6.44E+06	1.77*			2.44E+08	1.76*
MESS_12Y:10Y			6.75E+06	1.6			5.74E+08	3.99***
TRANS_10Y			2.50E+06	1.35			9.14E+06	0.23
TRANS_12Y:10Y			2.70E+06	2.49**			2.81E+07	0.87
PARTICIPANTS			2.71E+07	1.94*			1.38E+09	3.83***
MACRO			-1.63E+06	-0.27			-5.31E+08	-4.3***
O:I_10Y			1.91E+06	0.35			-1.09E+09	-5.65***
Adj R^2	18.49%		24.93%		71.89%		84.56%	
N	658		637		658		637	
Specification	FE		FE		FE		FE	

Notes: This table reports the results of the DiD panel regression model specified in Equation 3.19 using *TWQD* and *TWQD10* as dependent variables. *(1)* presents the DiD model without controls while *(2)* presents the same specification with controls. *Event* is a dummy variable that takes the value 0 for the pre-BRC period [d_{-160} = 1 August 2014, d_{-1} = 30 March 2015] and 1 for the post-BRC period [d_0 = 31 March 2015, d_{170} = 30 December 2015]. *Treatment* is a dummy that takes the value 1 for benchmark grade swaps (10Y) and 0 otherwise (12Y). *Interaction* is a dummy variable computed as $Event \times Treatment$. *SRVIX* is the log return on the Interest Rate Swap Volatility Index. *TYVIX* is the log return on the 10-year US Treasury Note Volatility Index. $MESS\_10Y$ is the log daily count of the number of messages received by the platform operator for the 10Y IRS contract. $MESS\_12Y : 10Y$ is the log ratio of messages for the 12Y contract relative to the 10Y contract. $TRANS\_10Y$ is the log daily number of transactions in the 10Y IRS contract. $TRANS\_12Y : 10Y$ is the log ratio of the number of transactions in the 12Y contract relative to the 10Y contract. *PARTICIPANTS* represents the log number of USD streamers per trading day. *MACRO* is a dummy variable that takes the value 1 on days with macroeconomic announcements by the FOMC and the Governing Council of the ECB and 0 otherwise. *O:I_10Y* is the log ratio of outright to implied messages in the 10Y IRS contract. The models are estimated using tenor fixed effects. We use Driscoll and Kraay (1998) consistent standard errors. Robust t-statistics are shown in the *t-Stat* columns. *, **, and *** correspond to statistical significance at 10%, 5%, and 1% levels respectively. Sample period is 01.08.2014-30.12.2015.

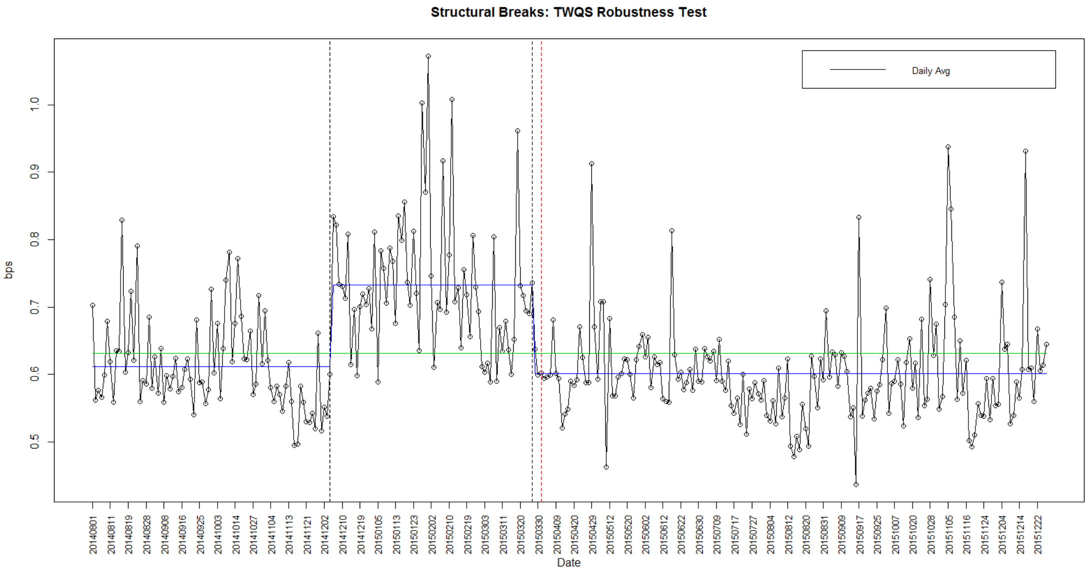
Figure A.4. Benchmark differential



Notes: This figure shows the development of the daily differential between the 10Y benchmark rate and the on-platform mid-price for the 10Y USD IRS using a two-tiered approach (see below). The black dotted lines mark the break dates as determined by the BP model. The green line depicts the long-term average of the time series, while the blue line shows the segment averages. The red dotted line marks the event date [d_0 = 31 March 2015]. *Pre-BRC* refers to the ISDAFIX regime [d_{-160} = 1 August 2014, d_{-1} = 30 March 2015]. *Post-BRC* refers to the ICE Swap Rate regime [d_0 = 31 March 2015, d_{170} = 30 December 2015]. For the ISDAFIX period, the differential is calculated based on the benchmark rate and the point observation of the quoted mid-price at 11 am. For the ICE Swap Rate period, the differential is computed based on the benchmark rate and the average quoted mid-price during the two-minute benchmark assessment. All values are expressed in bps (1 bps = 0.01%).

Figure A.4 illustrates the outcome of the Bai and Perron (BP) multiple structural break test on the time series of the benchmark differential. The BP model establishes that breaks occur on 1 December 2014 and 25 March 2015. On 1 December 2014, the Financial Conduct Authority (FCA) published the Consultation Paper CP14/32, discussing the inclusion of additional benchmarks in the regulatory and supervisory regime. The break on 25 March 2015 arises four trading days before the effective date of the benchmark regime change (BRC). The benchmark differential dropped on this date and settled at a significantly lower level thereafter. It should be noted that, during the four days from 25 March to 31 March, the benchmark rate was still relying on the panel-based assessment methodology. This finding suggests that a change in submission behavior might have occurred slightly before the introduction of the market-based benchmark assessment. Panel banks potentially geared the submitted rates more strongly towards the price quoted on regulated trading venues.

Figure A.5. Robustness test: Identification of structural breaks



Notes: This figure shows the development of the *TWQS* for the 10Y USD IRS over the sample period. I use a trimmed time series in order to exclude extreme days such as macroeconomic outliers. The black dotted lines mark the break dates as determined by the BP model. The green line depicts the long-term average of the time series, while the blue line shows the segment averages. The red dotted line marks the event date [d_0 = 31 March 2015]. *Pre-BRC* refers to the ISDAFIX regime [d_{-160} = 1 August 2014, d_{-1} = 30 March 2015]. *Post-BRC* refers to the ICE Swap Rate regime [d_0 = 31 March 2015, d_{170} = 30 December 2015]. All values are expressed in bps (1 bps = 0.01%).

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IF I HAVE SEEN FURTHER it is by standing on ye sholders of Giants.

Sir Isaac Newton

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