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The Visible Hand: Benchmarks, Regulation and Liquidity*

Matteo Aquilina[†], Gbenga Ibikunle[‡], Vito Mollica[§], Andrea Pirrone[¶] and Tom Steffen^{||}

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ABSTRACT

We present a model showing that a more precise benchmark assessment can improve welfare by overcoming traders' and the regulator's inability to penalize the dealers sufficiently. The empirical analysis of the change from the panel-based benchmark assessment under the ISDAFIX regime to the market-based assessment under the ICE Swap Rate regime and the contemporaneous start of regulatory supervision by the UK Financial Conduct Authority (FCA) confirms the theoretical predictions. Studying proprietary order book data of electronically-traded USD interest rate swaps, we find that liquidity in the underlying market improves following the benchmark regime change. Our results are robust to a multitude of controls and show that the enhancement in liquidity for swaps with a regulated benchmark assessment is over and above the improvement in those swaps without assessment. 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

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[†]Financial Conduct Authority, matteo.aquilina@fca.org.uk.

[‡]University of Edinburgh, Business School. gbenga.ibikunle@ed.ac.uk.

[§]Macquarie University, Graduate School of Management, vito.mollica@mgsm.edu.au.

[¶]Financial Conduct Authority, andrea.pirrone@fca.org.uk.

^{||}Corresponding author: Tom Steffen; Macquarie University, Graduate School of Management and University of Edinburgh, Business School, 29 Buccleuch Pl, Edinburgh, Lothian EH8 9JS; Email: tsteffen@cmcrc.com. Contact number: +44(0)754 1911496. Tom thanks the Capital Markets Cooperative Research Centre (CMCRC) and the Australian Government Research Training Program Scholarship for funding a period as a visiting researcher at the FCA during this study.

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 executions, and signal the prices available in the market. For example, instruments such as mortgage and credit card rates are influenced by benchmarks such as LIBOR (London Interbank Offered Rate). They also serve as reference rates for fund managers and increase price transparency for investors. Information asymmetries, market power and design inefficiencies may, however, prevent markets from working well (Iscenko, Andrews, Dambe, and Edmonds, 2016). Nonetheless, until very recently, benchmarks were not subject to any regulation. This changed in 2013, after the well-publicized scandals in relation to LIBOR, and later the WM/Reuters FX benchmark, the LBMA Gold Price and the ISDAFIX rate, when the Financial Conduct Authority (FCA) started regulating a total of eight benchmarks.¹

Recent theoretical work by Duffie, Dworzak, and Zhu (2017) shows that a benchmark improves the matching process in opaque over-the-counter (OTC) markets. The authors demonstrate that the introduction of a benchmark can enhance social welfare as it improves the information available to traders and reduces their search costs leading to increased price transparency.² For this reason, a benchmark encourages dealers to compete more 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. The authors show that a benchmark thereby stimulates greater entry by traders while at the same time “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) compare the case where a benchmark exists to the case where it does not, leaving no room for a theoretical analysis of the economic effects of an increase in the “quality” of the benchmark - a likely result from the aforementioned regulations. In this paper, we fill this gap by modeling the regulatory intervention as a reduction in noise which is brought about by an increase in precision in the benchmark fixing process. Our results imply that the appropriate regulation of a benchmark can be positive for the market, and provide a solid theoretical rationale to many of the recent interventions in this area.

In our model, traders cannot observe dealers’ marginal costs but, as in Duffie et al. (2017), they can observe a public signal aggregating the information (the benchmark). Differently from Duffie et al. (2017), in our setting, the benchmark is measured with noise. The noise represents traders’ different interpretations of the same signal (because of a lack of precision in the benchmark fixing) and imperfections of the benchmark assessment between the dealers themselves (because of a lack of quality of the production costs data). Due to the information asymmetry between dealers and traders, traders have to pay more than the efficient cost, and this reduces social welfare. To solve this problem, traders and regulators can decide to “punish” the dealers if the benchmark realization shows they are taking advantage of their position (by charging a high price). But 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 is for traders to pay a price close to the cost of production. We show that a policy that reduces the noise in the benchmark fixing process by increasing precision overcomes these limitations and restores the optimal outcome. In practice, such a policy would be very similar to the imposition of systems and controls that was central to the rules introduced by the FCA in 2013 and 2015.

We then examine the benchmark regime change (BRC) induced in 2015 by the FCA in the interest rate swap (IRS) market. Based on our model, we hypothesize that the reformed benchmark has positive effects on the liquidity of the underlying swap market. Specifically, we focus on the 31 March 2015 transition from the unregulated panel-based ISDAFIX benchmark to the regulated market-based ICE Swap Rate. The benchmark is crucial for swaps used, for example as hedging instruments for interest rate risk, and the size of which market is estimated at \$289 trillion in notional amounts outstanding. A regulatory change to the benchmark of this economically sensitive instrument therefore might have far reaching consequences.

Focusing on USD swaps, we find that the BRC has a positive effect on the representativeness and thus the accuracy of the benchmark rate. We measure this as the differential between the execution price of a standard market size (SMS) trade on-platform and the benchmark itself. Following the benchmark regulation, the assessed rate is closer to actual electronically executed trades on swap trading platforms. More importantly, we also show that market liquidity improves following the BRC, as measured by quoted spreads, depth and execution costs. Spreads have narrowed significantly by 14%. Despite quoted depth at the best bid and offer decreasing, the overall 10-level order book depth has slightly increased and the book has become consolidated, enabling cheaper executions of SMS orders. The approximated roundtrip costs for completing a buy transaction and a sell transaction have 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. 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 by so called “streamers”³. We therefore directly link the improvement in on-platform execution costs to the regulatory intervention of the FCA. Our results are robust to controlling for a multitude of confounding effects such as volatility and macroeconomic events and alternative regression specifications. Moreover, we also endogenously test for structural breaks in the time series of the employed liquidity measures and identify significant breaks imminently ahead of the BRC.

Our paper relates to the academic literature stream on financial benchmarks and their interactions with the underlying markets.⁴ However, existing research mostly focuses on trading patterns of financial products around benchmarks and potential issues caused by their assessment, starting with LIBOR, and then evolving to include precious metals, oil, and foreign exchange benchmarks. [Abrantes-Metz, Kraten, Metz, and Seow \(2012\)](#) study the market dynamics around 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 understated their LIBOR submissions and present evidence that this behavior likely led to a reduction in the reported rate. Meanwhile, [Fouquau and Spieser \(2015\)](#) apply a novel technique allowing them to detect possible cartels, which align with the manipulating banks that have been fined by regulators for their role in the 2012 LIBOR scandal. In the precious metal market, [Caminschi and Heaney \(2014\)](#) deduce that information is leaking from the physical London PM Gold price fixing into the gold derivatives market ahead of the official price publication. In a similar study of the assessment of the less known but highly influential Dated Brent spot oil benchmark, [Frino, Ibikunle, Mollica, and Steffen \(2017\)](#) report evidence of a consistent price trend of the Brent futures in the direction of the benchmark outcome during the on-going assessment. [Aspris, Foley, Grattan, and O’Neill \(2015\)](#) conclude that the incremental transition from the traditional manual auction for gold and others to the more transparent electronic-based auction led to a measurable improvement in market quality of the related financial derivatives. While their study is similar in nature to ours, we believe that the evolution of the ISDAFIX benchmark to the ICE Swap Rate is more suitable for an event study of this type, since the benchmark assessment was overhauled in a single clear-cut move from panel submissions to a regulated market-based assessment. Finally, the papers by [Osler \(2016\)](#) and [Evans \(2016\)](#) focus on foreign exchange and the WM/Reuters London 4pm 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 issues raised in the academic literature are a source of concern for market participants and regulators alike. Hence, this research stream led to a set of papers focusing on the reform of financial benchmarks and the benchmarks’ value for financial markets (see for example [Duffie et al., 2017](#); [Perkins and Mortby, 2015](#)).

With this study, we wish to complement this literature and make three contributions. Firstly, we suggest a model that theoretically motivates the recent regulatory interventions and the expected improvements to both benchmarks and markets. Secondly, our paper is, to our knowledge the first to empirically test our own model, as well as recent theoretical work by [Duffie et al. \(2017\)](#) about the effects of benchmarks on market quality. Thirdly, we add to the debate on the impact of regulatory interventions on the efficient functioning of financial markets. Finally, our proprietary full order book data set, covering roughly 50% of the electronic inter-dealer IRS market, allows us to directly analyze and document the microstructure of the world’s largest derivatives market in academic literature for the first time.

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

II. The Model

A. Structure of the model

We start with a market with 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 search costs. The timing of the game is as follows:

- Nature draws dealers marginal costs, traders search costs, and the benchmark realization;
- Dealers move first and set the price of the good;
- 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 good and pays 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 dealers' market. Again, the noise in the benchmark fixing can be the result of traders' different inferences or dealers' discovery processes of their marginal costs. Therefore, rules similar to those implemented by the FCA in 2013 and 2015, which brought benchmarks into the regulatory perimeter for the first time, and often amended their assessment process, would have the likely effect to reduce such noise.

The benchmark y is therefore defined as

$$y = \sum_{i=1}^n \frac{a_i}{n} + \epsilon \quad (1)$$

where $\epsilon \sim F(0, \sigma^2)$ is the noise component, with density f and cumulative distribution F . As $\sigma \rightarrow 0$, 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

$$p_1 \leq p_2 \leq \dots \leq p_n$$

We assume that traders expect to find any of the prices with equal probabilities.⁵

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

The price distribution is common knowledge among traders, but traders don't know whether the price charged by the next dealer will be higher or lower if they continue searching. For tractability, we also assume a trader can always go back to a previous dealer.

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

$$G(x) = \begin{cases} \frac{x}{s} & \text{if } 0 \leq x \leq v - p^* \\ \frac{v-p^*}{s} & \text{if } x > v - p^* \end{cases} \quad (2)$$

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 $0 \leq x \leq v - p^*$.

In equilibrium each trader j stops searching and pays p_i when the expected gain from searching a price lower than p_i equals j 's search costs. The expected gain from searching a price lower than p_i is the sum of gains weighted by the probabilities of finding a dealer with a price lower than p_i : $\sum_{k=1}^{i-1} (p_i - p_k) Pr(p_k)$. The equilibrium condition is therefore:

$$x_j = \sum_{k=1}^{i-1} (p_i - p_k) Pr(p_k) \quad (3)$$

where p_k represents all prices lower than p_i .

Let q_i be the quantity demanded to a dealer with price p_i . A dealer with price p_i sells to two groups of traders:

- Traders who randomly found p_i , despite the fact they would have been willing to pay a price $p_{i+1} > p_i$ (the demand of dealers with prices higher than p_i);
- Traders with search costs higher than the expected gain from searching a price lower than p_i .

Both types of traders are represented formally in the equation below

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

Using the equilibrium condition (3), the expected demand for the dealer with price p_i simplifies in (Carlson and McAfee (1983) provide the proof, but we reproduce it in the appendix)

$$q_i = \frac{v - p_i}{sn} \quad (4)$$

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 adjusted by traders' density and the number of dealers on the market (sn).

D. Prices

As in [Duffie et al. \(2017\)](#), traders can exit the market if they infer that dealers are overcharging them by observing a realization of the benchmark lower than a certain threshold⁷. If traders leave the market, demand drops and dealers need to charge a lower price. We model this behavior using the penalty parameter Δ ⁸. In the next section, we will model what happens as the threshold \bar{y} changes, but we focus on dealers' profits for the time being.

Profits of dealer i are

$$\pi_i \equiv \left[F\left(\bar{y} - \frac{\sum_i a_i}{n}\right) (p_i - \Delta) + \left(1 - F\left(\bar{y} - \frac{\sum_i a_i}{n}\right)\right) p_i - a_i \right] q_i \quad (5)$$

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.

Competition among dealers drives their profits to 0, from (5) it follows that

$$p_i = a_i + \Delta F\left(\bar{y} - \frac{\sum_i a_i}{n}\right) \quad (6)$$

and from (4), $q_i = \left[v - a_i - \Delta F\left(\bar{y} - \frac{\sum_i a_i}{n}\right) \right] / sn$, which clarifies that traders punish the dealers by exiting the market when they infer the marginal costs are below the threshold (and so dealers overcharge them).

Each dealer i sets the price p_i to minimize the penalty Δ , which yields (the proof is in the appendix):

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

And, substituting this back into (6), we obtain

$$p_i = a_i + n \frac{F\left(\bar{y} - \frac{\sum_i a_i}{n}\right)}{f\left(\bar{y} - \frac{\sum_i a_i}{n}\right)} \quad (7)$$

Therefore, dealers add a mark-up on top of the cost of production to determine the price at which they are willing to sell. In the moral hazard literature, this mark-up is known as "information

rent” as it relies on dealers’ information advantage.

E. Threshold and precision

We can now analyze traders’ behavior as the threshold \bar{y} changes (as in [Holmstrom \(1982\)](#)). We assume F is normally distributed. Then, from (7), as traders decrease the threshold at which they would leave the market (i.e. $\bar{y} \rightarrow -\infty$), the penalty for dealers increases ($\Delta \rightarrow +\infty$), and $F\left(\bar{y} - \frac{\sum_i a_i}{n}\right) / f\left(\bar{y} - \frac{\sum_i a_i}{n}\right) \rightarrow 0$, implying that traders achieve their first best $p_i = a_i$ in which dealers don’t charge any mark-up at all.

However, traders cannot achieve $\bar{y} \rightarrow -\infty$ as production costs cannot be negative; and an external authority (e.g. the regulator) cannot achieve $\Delta \rightarrow +\infty$, as this level of regulatory fines is simply impossible.

There are other ways in which the outcome can be moved towards the optimal one: by reducing the noise in the benchmark fixing. To see this, 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 we obtain the following equation for the price set by each dealer i ⁹:

$$p_i = a_i + n\sigma \frac{h(\zeta)}{h'(\zeta)} \quad (8)$$

where $\zeta \equiv \frac{\bar{y} - \frac{\sum_i a_i}{n}}{\sigma}$, and $h(\zeta)$ is ζ ’s density function.

Therefore, an increase in precision reduces the noise in the benchmark fixing process (σ) and moves the outcome closer to the first best. If the noise in the benchmark fixing process is eliminated, i.e. $\sigma = 0$, then the first best can be achieved irrespectively of the level of penalties. In such a case, traders pay a price that matches the exact cost of production of each dealer.

Our 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 where traders use the benchmark to monitor the dealers. The noise in the benchmark fixing allows the dealers to extract a rent, but traders cease trading with the dealers if they can infer dealers are taking advantage of the information asymmetry. In this market, a policy decreasing the noise in the benchmark fixing is welfare improving.

III. Institutional Details and Data

A. *The Swap Market*

Fixed-for-floating interest rate swaps (henceforth also simply referred to as swaps) are nowadays mainly traded on regulated trading venues, where buyers and sellers meet to exchange cash flows calculated based on a notional amount, with one party paying the fixed rate and receiving the floating rate and vice versa. Therefore, each payment series of a swap is defined as a leg, a fixed leg and a floating leg. Given the prominence of USD IRS, which are the most popular interest rate derivatives with a notional amount outstanding of \$139 trillion¹⁰, we focus on the USD segment of the swap market. 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 facility (SEF).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 derivatives, such as swaps, on regulated venues to promote competition and to enhance transparency. As such, SEFs are electronic trading platforms that post and execute bid and offers to trade swaps of multiple participants. Under the mandatory trade execution requirement, swaps made available to trade (MAT)¹² are required to be traded on SEFs from the effective date of February 2014 onwards, which pre-dates our sample period.¹³ A list of the USD IRS maturities captured by the MAT mandate can be found in Table I. Recent statistics estimate that two thirds of fixed-for-floating IRS trading nowadays takes place on-SEF.¹⁴

[Place Table I about here]

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

In the US, numerous firms operate SEFs and generally speaking, the trading venues are either inter-dealer brokers (IDB) such as Tradition and BGC Partners, or dealer-to-client platforms such as those operated by Bloomberg and Tradeweb. This split, often referred to as bifurcation by market participants, is a feature of the swap market allowing dealers to interact with each other on one platform and to serve their clients on another platform. Nevertheless, under the Commodity Exchange Act of Dodd-Frank SEFs need to provide impartial access to all eligible participants in a transparent and non-discriminatory manner. Industry estimates indicate that for IRS the market share split between the dealer-to-dealer and dealer-to-client segments is 40% and 60% respectively, although these numbers fluctuate depending on tenor and currency.

B. *The Regulation of Benchmarks*

The economic significance of the IRS market and its high degree of interconnectedness with the fixed income and money markets amplify the importance of swaps to the global financial markets.

Hence, the need for a reference price in the form of a standardized benchmark rate to value and settle contracts was recognized early on. The ICE Swap Rate, formerly known as the ISDAFIX rate, is of crucial importance to these markets, as it 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 by a panel of sixteen banks representing the mid-market rate at which they were willing to trade a SMS swap. 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 our sample. The benchmark submitters were asked to submit a live mid-market rate derived from their own bid/offer spread in the current market environment. For USD swaps, the panel submission polling window ranged from 11:00:00 to 11:15:00 ET and the ISDAFIX rates were published at 11:30:00 ET (see Panel B of Figure 1).¹⁵ To establish the daily benchmark rates, a trimmed mean of the submitted rates was computed, depending on the number of bank participants.

On 1 August 2014, ICE Benchmark Administration (IBA) took over full responsibility from ISDA for USD, EUR, and GBP assessments, but kept 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 benchmarks.

On 31 March 2015 IBA completed the transition from the submission-based assessment system to an automated and market-based methodology and assessed the benchmark rates for the first time relying on *tradable* quotes from regulated electronic trading venues. The benchmark was renamed ICE Swap Rate taking effect 1 April 2015.¹⁶ The methodological change went hand-in-hand with the introduction of regulatory supervision by the FCA starting 1 April 2015. A timeline of events is illustrated in Panel A of Figure 1.

[Place Figure 1 about here]

The ICE Swap Rate is the principal global benchmark setting the fixed leg price for IRS at a certain time of the 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 a SMS¹⁷ trade, based on the best available prices across trading venues collected from 10:58:00 to 11:00:00 ET, with the rate being published at 11:15:00 ET (see Panel C of Figure 1).

The two-minute data collection window is divided into 24 blocks of 5 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 a SMS order. This process is repeated for each snapshot time and after discarding illiquid and outlier snapshots the remaining snapshots are quality-weighted¹⁸ to calculate the ICE Swap Rate.

C. Data and Study Design

For the USD ICE Swap Rate assessments, IBA collects data from three of four trading venues, namely Trad-X (Tradition), BGC Trader (BGC Partners) and i-Swap (ICAP).¹⁹ For the period of our investigation, Tradition is the market leader in the IDB segment, accounting for a market share of over 50%, although this number fluctuates depending on the currency and swap tenor.²⁰

Due to the sheer size of the order book, with over 30 million messages per day, tenor and currency, we obtained the full order book data of the Trad-X SEF for LCH cleared swaps from Tradition (UK) Ltd only.²¹ All usual order book variables and all USD tenors, ranging from 1 to 50 years, are recorded in the data. The time period starts on 1 August 2014, when IBA took over the benchmark assessment, to 30 December 2015, a total of 331 trading days.²² In our proprietary data, the 10Y USD swap is on average the most liquid tenor with respect to quote submissions and transactions and therefore the target of our analysis. We 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 9:30am to 4pm ET.

Messages consist of three action types; new order submissions, changes, and cancellations and are timestamped in GMT to the nearest millisecond (ms). Given the USD emphasis, we convert all our time references to local New York Eastern Time (ET). Each message is labelled with a unique order identifier, allowing us 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 enabling us to correctly trace the unfolding of events.

Both outright, as well as implied orders are recorded and as tradable quotes they both contribute to the ICE Swap Rate assessment. This distinction of orders is very frequently employed in the swap market. An outright order is a direct price submission by a trader in a specific contract, such as an individual swap contract. An implied order is generated from the price differential between two existing contracts. For example, the differential of the known prices of two swap tenors goes into generating the unknown value, the spread between the two, thereby generating a tradable implied order. The Trad-X platform includes an implied engine, which produces implied orders along the swap curve, substantially enhancing market liquidity. We also receive reports of electronically executed transactions. On the Trad-X platform, approximately 25% of transactions are executed electronically, while 75% of transactions are concluded via the voice functionality.

The market-based assessment of the ICE Swap Rate by IBA using tradable quotes from limit order books of regulated electronic trading venues was conducted for the first time on 31 March 2015. On 1 April 2015 the FCA started regulating the ICE Swap Rate. We employ an event study methodology, where the 31 March 2015 is the event day, t_0 . The ISDAFIX regime encompasses $[d_{-160} = 1 \text{ August } 2014, d_{-1} = 30 \text{ March } 2015]$. The ICE Swap Rate regime extends $[d_0 = 31 \text{ March } 2015, d_{170} = 30 \text{ December } 2015]$. We refer to the period before the change to the benchmark assessment methodology and regulation as *pre-BRC* and the period after this date as *post-BRC*.

IV. Electronic Trading of Interest Rate Swaps

Before discussing the effects of the regulation and change in methodology we begin with a brief description of the data at our disposal. The midpoint price (where the price of a swap is a percentage rate) in the 10Y USD IRS is depicted in Figure 2. The shaded area represents the period after the regime change. Overall the pre-BRC (post-BRC) period includes 160 (171) trading days. The average quoted mid-price for a 10Y USD swap before 31 March 2015 is 2.33 and the average best bid and offer (BBO) quote size amounts to 50.66 million. After the 31 March 2015 (inclusive), the average mid-price and BBO quote size are 2.21 and \$45.18 million respectively. The period of investigation was characterized by significant price volatility due to several macroeconomic and political events. The average daily price volatility (measured by the standard deviation of the mid-price) during the pre- and post-period amounts to 0.24 and 0.15 respectively, and is thereby lower after the event date. We control for price volatility in our analysis. Although the size of the submitted BBO quotes is smaller, there is also less variability in their size (\$40.52 million versus \$37.14 million).

[Place Figure 2 about here]

Descriptive statistics of quotes and transactions can be found in Table II and Table III. For the 10Y swap contract, a total average of 30.27 million messages is recorded every day on the Trad-X platform. The messages are split between implied and outright orders. Due to the nature of the IRS market, characterized by interweaving swap curve and strategy dynamics²³, and the development of potent pricing engines by electronic trading venues, implied orders play an increasingly important role in the continuous pricing of products. It should be stressed that both outright and implied orders are firm and executable.

[Place Table II about here]

For the 10Y USD swap contract, on the average day, a total of 103,000 messages are related to outright orders, while the remaining 30.17 million messages are related to implied orders, accounting for more than 99% of total message flow. Of these 30 million messages, half accounts for new order submissions, while the other half corresponds to their respective cancellations. There are only very few order changes (an average of 2 change messages daily; see Table II). A cancel and replace message is faster and is effectively the same as a change message and, given the paucity of transactions time priority is unlikely to be an important factor.

Our data include only electronically executed transactions, which account for approximately 25% of all transactions on this platform. In discussions with market participants, the platform was described as the ‘shop window’, attracting traders’ attention. The traders then often use the voice functionality of the platform to conclude transactions. Nevertheless, the electronic and voice systems of the trading venues are closely interlinked. As such, price innovations in one execution method are likely reflected in the other method too.

Given the large number of messages, trading on regulated SEFs is characterized by a very low trade-to-quote ratio. 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. For example, a transaction in the 10Y versus 12Y curve spread leads to individual executions in the 10Y leg and 12Y leg. As such, during the full sample period there were only 165 direct 10Y USD swap trades, averaging less than 1 transaction per day. However, the average daily total number of transactions in the 10Y USD swap leg contract on this platform is 21, while a total number of 6,835 transactions have been executed over the same period. The average trade volume of \$54 million is considerable, leading to a non-negligible total average daily executed volume of \$1.14 billion. Overall, between August 2014 and December 2015 a total volume of \$370 billion in 10Y USD swaps was traded electronically on Trad-X alone. For the rest of this paper, we will consider all transactions in the 10Y IRS, direct executions as well as executions in the individual 10Y leg as an element of a packaged trade.

[Place Table III about here]

The total number of messages as well as the number of outright messages have gradually increased over time; given that the large majority of messages are implied, the evolution of total and implied messages is identical. Pre-BRC, an average total of 25.89 million messages was recorded on the Trad-X platform for 10Y swaps, compared to 34.37 million messages in the post-BRC period (a rise of 33%). Outright order submissions increased by 26% from 91,000 to 115,000. With regard to transactions, the average daily number of 10Y USD IRS transactions has grown by 7% from 20 to 22, while average volume per transaction has remained stable (negligible change from \$54.23 million to \$54.10 million). The post-BRC period saw an increase in transactions by 14% to 3,650 compared to 3,190 for the pre-BRC period. The total volume traded likewise expanded from \$173 billion pre-BRC to \$197 billion post-BRC, a gain of 14%.

In summary, the vast majority of messages recorded are implied orders, most of which are cancelled during the trading day without being traded upon. Electronic trades are infrequent but considerable in terms of value. Nevertheless, the firm nature of 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, Hillion, and Spatt \(1995, 1999\)](#), where the efficient price is discovered in a gradual learning process of submitting additional buy and sell orders. The order flow in itself is informative [Biais et al. \(1995, 1999\)](#).

V. The Power of Benchmarks: Implications on Market Quality

We now move to discussing the observed effects on the quality of the swap market. [Duffie et al. \(2017\)](#) suggest that transparency in the sense of signalling price availability leads to enhanced dealer competition and better dealer-trader matching with positive effects on market liquidity. Our

model contends that the increase in benchmark accuracy through the transition to a market-based assessment and regulatory oversight has positive effects on the underlying market. We therefore test the hypothesis that liquidity measures reflect an improvement after the transition to the ICE Swap Rate regime.

A. A More Precise Benchmark?

We first analyze whether the benchmark is more accurate, in the sense that the new benchmark regime shifted the benchmark rate closer to market fundamentals. We test the hypothesis that the BRC leads to an improvement in the representativeness of the rate. To do this, our data set allows us to compare the benchmark rates under the ISDAFIX regime and under the IBA regime to market prices available on regulated trading venues.

To measure changes to the quality of the benchmark, we developed a simple measure which we label Benchmark-to-Market Differential (*BMD*). The ISDAFIX ahead of 31 March 2015 represented the rate at which dealer banks were willing to buy and sell a swap of a 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 a representative price for the execution of a SMS trade, both under the ISDAFIX regime and under the ICE Swap Rate Regime.

We define the *BMD* simply as:

$$BMD_{t,d} = |R_d - F_{t,d}| \tag{9}$$

where R_d is the assessed benchmark rate on day d and $F_{t,d}$ is the estimated average of the buy and sell price for a SMS order at second t , on day d , and computed as the average of F_t^A and F_t^B . F_t^A (F_t^B) is the hypothetical execution price for a 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 rate that is indicative of market fundamentals.

The pre and post values in Table IV report the average daily *BMD* during the ISDAFIX and the ICE Swap Rate regime 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 minutes versus 2 minutes). For reasons of comparability and robustness, we average the $BMD_{t,d}$ over multiple windows of different length (1 min, 10 mins, 30 mins etc.) centered on the 11am assessment in order to provide a comprehensive picture of the representativeness of the rate.

By means of example, for the 11am window in Table IV we calculate the *BMD* at each second t for the 1-minute window from [11:00:00; 11:00:59]. We then compute the window mean and average across days within the pre- and post-period. The result indicates that for this particularly short window, an on-platform execution of a 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 on the basis of which the administrator calculated the benchmark rate. Submissions opened and concentrated at 11am and thus by construction, the difference between the assessed rate and the market price at that point in time is small. The ICE Swap Rate, however, is essentially a 2-minute average of the market price from 10:58:00 to 11:00:00, introducing stronger sensitivity to price movements, and therefore by construction a larger differential to the market price is observed at 11am.

[Place Table IV about here]

Hence, we argue that a comparison of the benchmark rate to the estimated average execution price for different time windows centered on 11am is most meaningful. By extending the window length over which we compute the *BMD* measure, we find that post-BRC the benchmark rate is indicative of market prices for a longer period of time. 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 compared to the old regime. This finding is only statistically significant for the 10-minute window centered on 11am, although generally speaking we do see a pattern of a smaller benchmark differential under the ICE Swap Rate regime. Based on the 10-minute window, we can accept the hypothesis that the BRC did positively affect the representatives of the benchmark rate at the 5% significance level. Moreover, the benchmark-to-market differential at the respective assessment ends and publication times of the ISDAFIX and ICE Swap Rate regimes is significantly smaller under the new benchmark regime (a reduction of 68% and 22% respectively); results which are statistically significant at the 1%-level.

We want to highlight the findings for the 10-minute window immediately preceding the start of the benchmark assessments too. The benchmark rate should be indicative of where the dealers see the market price at the time of the assessment and the quote submissions ahead of the assessment start should thus be indicative of 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 from [10:48:00; 10:58:00] is 15% smaller during the post-BRC period compared to the pre-BRC period. This development is statistically significant at the 5% level.

Overall, the results presented in Table IV show that the transition to the ICE Swap Rate improved the representativeness of the benchmark, and the rate is more precisely reflecting market conditions at the assessment end and publication time.

B. A More Efficient Price?

As suggested in Duffie et al. (2017), a benchmark can increase price transparency enabling traders to make better informed decisions and thus result in more intensive dealer competition on the quoted price. As a result, one would expect prices to be more efficient and to better reflect the information of the market participants. In order to test the informational efficiency, we follow an approach developed by Biais et al. (1995, 1999) called ‘unbiasedness regressions’. The level of price

efficiency for the 10Y swap is computed for both the pre-BRC as well as the post-BRC period by separately estimating Equation 10 and averaging the slope coefficients across seconds t .

$$r_{oc} = \alpha + \beta r_{ot} + \epsilon_{ot} \tag{10}$$

where r_{oc} is the open-to-close return for the time period of interest and r_{ot} is the return from the open of the chosen period to the second t . Since our interest lies on the benchmark assessment periods, we 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.

[Place Figure 3 about here]

Figure 3 reports the average slope coefficient estimates. As expected, during the first intervals of our estimation, the returns from 10:58:00 to interval t do not explain the total ‘10:58:00-to-11:30:00’ return well. Still, as time progresses it becomes apparent that noise decreases rapidly and the efficiency of the swap price 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 be achieved. By means of example, β approximately reaches unity at 11:04:00 in the post-regime (red line), while it only achieves similar levels roughly 15 minutes later in the pre-regime (blue line). Overall, the results suggest that in the post-BRC period price efficiency is enhanced compared to the pre-BRC period.

In the following sections, we analyze the extending implications of the BRC on market liquidity and corroborate that the improvement is indeed effected by the regulatory-driven change from the ISDAFIX rate to the ICE Swap Rate.

C. *A More Liquid Market?*

Previous work has found that greater transparency through better market infrastructure, changes in regulation, or enhanced reporting often leads to an improvement in market liquidity (see for example [Benos, Payne, and Vasios, 2016](#); [Trebby and Xiao, 2016](#)). In a similar vein, and following our model predicting that a more precise benchmark positively affects the underlying market, we examine the liquidity after the introduction of the ICE Swap Rate regime.

The quoted dollar spread is defined as the difference between the best bid and offer price computed for each second t .

$$QS_t = (A_t - B_t) \tag{11}$$

The relative quoted spread is determined as the ratio of the quoted spread and the quoted

mid-price. The relative spread is sensitive to movements in the market price, which in our case is volatile and on average lower during the post-BRC period (see Table II); hence we only use this measure to corroborate our results, since a lower price should lead to a larger relative spread if quoted spreads remain constant.

$$RQS_t = \frac{(A_t - B_t)}{M_t} \quad (12)$$

We also develop an additional measure of spread (which we label “fill spread”) which is useful in markets characterized by a LOB but very few transactions, such as the one we are 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 transaction and seller-initiated transactions and P_t is the transaction price. A trader could execute either a buy or a sell transaction. Since we simulate the filling of both a buy (F_t^A) and a sell (F_t^B) SMS order for each second, we do not need DIR_t . The hypothetical fill spread can thus be written as:

$$FS_t = (F_t^A - M_t) + (M_t - F_t^B) \quad (13)$$

But as the comparison to the mid-price in Equation 13 cancels out, it can be written as the difference between F_t^A and F_t^B in Equation 14. In other words, the fill spread measures the roundtrip costs for completing a buy transaction and a sell transaction approximating the liquidity on both sides of the order book at second t . Hence, our view is that this is the best measure of liquidity for our purposes.

$$FS_t = (F_t^A - F_t^B) \quad (14)$$

Quoted depth (QD) and 10-level quoted depth ($QD10$) 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 ($l = 1, \dots, 10$) of the order book respectively.

$$QD_t = (V_t^A + V_t^B) \quad (15)$$

$$QD10_t = \sum_{l=1}^{10} (V_{l,t}^A + V_{l,t}^B) \quad (16)$$

We time-weight all our measures, where LM_t represents one of the above described liquidity measures. t is the second timestamp of the $i = 1, \dots, N$ intraday quote update on day d . T is the length of the trading day.

$$TWLM_t = \frac{1}{T} \sum_{i=1}^N LM_t(t_{i+1} - t_i) \quad (17)$$

Figure 4 illustrates the quoted spread (red) on a second-by-second basis over the full sample period (1 August 2014 to 30 December 2015). On average, quoted spreads hover around 0.64 bps. The spikes in spreads mostly coincide with unusual market events (e.g. US treasury flash crash on 15 October 2014, CHF-EUR unpegging on 15 January 2015) or macroeconomic announcements

(e.g. a European Central Bank (ECB) announcement on 4 December 2014). As can be seen by the 1-hour moving average (green) and 5-hour moving average (blue), quoted spreads increase in early December 2014 and remain large for several months. Quoted spreads then narrow around the end of March 2015 and remain at lower levels for the rest of the year.

[Place Figure 4 about here]

In Table V, we report the long-term comparison of the liquidity measures by splitting the sample period before and after the exogenously-determined event date (please refer to the robustness section for the short-term liquidity effects). We 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 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%. Our results also hold if we use daily median values instead of mean values to account for potential skewness of the data.

[Place Table V about here]

We complement the spread analysis by studying market depth, both at the best bid and offer level as well as at the bid and offer of the full first ten levels of the order book. Columns 4 and 5 of Table V 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 (\$100 million versus \$90 million), a deterioration of 10% at the 1% significance level. On the other hand, 10-level quoted depth increases somewhat 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 using median values.²⁶

In short, spreads narrow and the order book at the first ten levels appears to be marginally deeper, but depth at the best level is thinner. Traders however are interested in the costs of trading. Consequently, in the third column of Table V, we report the results for the time-weighted fill spread ($TWFS$). 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. In addition, although not reported in this table, the total number of times that a SMS order can't be executed (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, corresponding to a drop of 63%.

D. Regulation as a Driver?

So far we have provided evidence that the quality of the swap market improved after the FCA started regulating the relevant benchmark, but we cannot infer that the regulation caused the changes. In this section, we address this shortcoming and attempt to determine causality to the extent possible. We do this by employing a difference-in-difference (DiD) approach and compare the changes in liquidity for tenors for which a regulated benchmark is calculated to tenors for which it is not. The panel regression models are therefore of the following form:

$$DV_{i,d} = \alpha + \beta_1 Event_d + \beta_2 Treatment_i + \beta_3 Event_d \times Treatment_i + \gamma' X_d + \mu_i + \epsilon_{i,d} \quad (18)$$

where i denotes tenors and d denotes days. The dependent variable DV corresponds to one of the two liquidity measures: $TWQS$ and $TWFS$.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. Our treated group is made up of tenors for which a benchmark is assessed. These tenors are therefore covered by the regulatory regime and benefit of 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 being assessed for the 12Y tenor (see Table I) while at the same time it is the most actively quoted and traded non-benchmark MAT tenor in our data.²⁸ X_d is a vector of control variables including swap and debt market volatility, venue participation, quoting and trading behavior, macroeconomic developments and others. β_1 captures any common effects that impact all swap tenors following the BRC. β_2 absorbs any pre-existing differences in characteristics between the treatment and control group. The coefficient of interest 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.

[Place Table VI about here]

Table VI reports the estimation results. The DiD model is estimated without controls and with controls (the columns are labelled as [1] and [2] respectively). We show that there is little difference in the coefficients of interest between the two specifications. Overall, our control variables help to explain a significant proportion of the development of our liquidity measures with an adjusted R^2 of 67% and 56% respectively.

Firstly, with the BRC there is an improvement in $TWQS$ for both groups of swap tenors, 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 beyond the improvement in the 12Y tenor. The $TWFS$ for the $Interaction$ coefficient reports that the execution

costs in the 10Y USD IRS have also come down significantly more than the execution costs in the 12Y USD IRS following the change in benchmark assessment methodology and regulation by the FCA. The results are equally strong for the model specifications with multiple controls, suggesting that the liquidity improvement is over and above other effects that affect swap market liquidity.

Both the quoted spread and the fill spread for all swaps widen on days with a surge in IRS volatility, and narrow on days with a rise in U.S. treasury note volatility (although not statistically significant). An increase in quoting activity (*MESS_10Y*) translates into significantly narrower spreads and execution costs. Trading activity (*TRANS_10Y*) has an inconsistent and mostly negligible effect on liquidity. The number of USD streamers (*PARTICIPANTS*), depicted in Figure 5, has a strongly positive effect on our liquidity measures. 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 of increased on-platform participation leading to a liquidity improvement, which is consistent with empirical microstructure findings (see for example [Barclay and Hendershott, 2004](#)). Unsurprisingly, macroeconomic announcement days (*MACRO*) are characterised by a significant widening of spreads and inflation of execution costs – in line with expectations, due to the increase in uncertainty on such days. Lastly, a change in the ratio of outright to implied orders (*O:I_10Y*), for example due to a reduction of implied quotes and therefore an increase in the ratio, leads to a widening of spreads.

[Place Figure 5 about here]

Importantly, even after controlling for a multitude of potentially confounding effects, our findings show a significant incremental improvement in on-platform execution costs for benchmark grade swaps. Taken together, our results suggest that at least part of the liquidity improvement was driven by the regulatory change and methodological evolution of the benchmark, and therefore confirm our hypothesis and the predictions of our 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 \$3.33 million to \$9.92 million.²⁹ The 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 to \$6.7 million. Given that we only focus on one tenor and that the swaps can be traded on other venues too, the overall benefits are likely to be substantially larger.

VI. Robustness Tests

A. Short Term Liquidity Effects

In the sub-section [V.C](#), we compare market liquidity before and after the regime change by exogenously identifying the potential break date. Changes to the microstructure of the underlying market could have occurred before or after the event date, leading to an improvement in quoted liquidity. We therefore use the event study methodology as employed in [Hegde and McDermott](#)

(2003) to take a closer look. We calculate our average 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] extending up to thirty trading days before the regime change. A period which is most likely unaffected by the BRC. If the ratio for the liquidity measure for some interval in Table VII is bigger (smaller) than unity, the interval average is greater (smaller) than the estimation window average. Given the similarity of findings for the three spread measures in Table V, we only discuss the *TWQS* here.

[Place Table VII about here]

The ratio using the average (median) time-weighted quoted spread for the interval $[0; 0]$ covering only the event date of the 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 spreads are significantly lower (5%-level to 1%-level) compared to their long-term average. During the eleven-day interval $[-5, +5]$ centered on the event date, average as well as median spreads are significantly lower with a value of 0.92 and 0.96 at the 1% and 5% significance level respectively. The results also hold for longer time periods, although at a non-significant level. 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 determined by the ratio of 0.89 at the 1%-significance level versus 1.08 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 is not significantly different from the reference value of the estimation window. In terms of 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), whereas the $[+1; +30]$ period shows a deeper order book (highly significant average ratio of 1.11 and median ratio of 1.12). The event study confirms our early findings suggesting that market liquidity reacted to the BRC, and has done so positively.

B. Structural Breaks

So far we relied on an exogenous determination of the event date to assess the implications of the BRC on liquidity. Namely we calculated our measures before and after the changes introduced to the methodology and the regulation of the benchmark. In this subsection, we statistically determine structural breaks in the liquidity measures endogenously. We follow the approach by

Bai and Perron (BP, 1998, 2003), the application of which is described in detail in Zeileis, Kleiber, Krämer, and Hornik (2003). The model set-up is based on a standard linear regression of the form:

$$y_t = x_t^T \beta_t + \mu_t \quad (t = 1, \dots, n) \quad (19)$$

where y_t and x_t correspond to the values of the dependent and explanatory variables respectively at time t (here days). β_t is the regression coefficient which can vary over time. The model tests the null hypothesis of the coefficient remaining constant over time, versus the alternative of a change in the coefficient over time:

$$H_0 : \beta_t = \beta_0 \quad (t = 1, \dots, n) \quad (20)$$

Assuming that there are m breakpoints in the time series where the mean of the coefficient is moving from one long-term level to another, 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 compares 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 breaks partitions provides the overall minimal residual sum of squares compared with one additional segment.

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

Figure 6 depicts the determined structural changes in the time series of four different liquidity measures.

[Place Figure 6 about here]

The *TWQS*, *TWFS* as well as *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. We have identified two potential reasons for this change: 1) ECB president Mario Draghi announcing a potential quantitative easing intervention or; 2) 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 5), which could also be the cause for the observed widening of spreads. The number of dealers recovers to its previous level on the next day and stays relatively stable thereafter, but clearly liquidity does not recover. However, participation over the following days is volatile possibly

explaining the wider spreads throughout the months of December to March. The downward second 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 break models are usually applied on less granular data (often monthly), we attribute this change in the long-term pattern to the imminent change in benchmark regime. There was also no major macroeconomic event around the break day (to the best of our knowledge). [Duffie et al. \(2017\)](#) 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, we 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 this argument. [Figure 5](#) illustrates that the number of platform participants remains above its long-term average during the large majority of the post-BRC period.

[Place [Figure 5](#) about here]

The breaks determined for the two depth measures are somewhat 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 before, but this time the March break occurs five trading days before the BRC. In general, the fact that all liquidity measures identify a break in the long-term time series imminently before the ISDAFIX regime was replaced by the ICE Swap Rate regime supports our earlier findings. It is likely that we observe joint effects of the positive consequences of benchmarks on financial markets predicted in our model and the work by [Duffie et al. \(2017\)](#).

VII. Conclusion

Our model provides a theoretical underpinning to many of the interventions in the space of benchmarks in recent years. By increasing the controls in the benchmark fixing process and by reducing the possibility of manipulation, benchmarks send a more precise signal to the market leading to better (or even optimal) market outcomes. This is in line with other work suggesting that benchmarks can increase social surplus and have positive welfare implications (see [Duffie et al., 2017](#)).

Testing our hypothesis, we find that 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 measurable improvement in market liquidity, translating into reduced execution costs for participants. The cost savings for electronic transactions in the 10Y USD interest rate swap from April 2015 to December

2015 on the Trad-X platform alone approximately amount to \$4 to \$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. Yet the effect is stronger for tenors for which a benchmark rate is assessed daily and which are presumably impacted more by the change in benchmark regime compared to other tenors. Hence, our results suggest that the influence of the regulatory regime is beyond the effect of confounding events such as increased venue participation. We also find that the accuracy of the benchmark itself has improved following the regulatory change.

There are two limitations to our study. First, we only analyze the order book data of the major inter-dealer platform contributing quotes to the ICE Swap Rate benchmark assessment. Developments in market quality on the remaining contributing venues, and dealer-to-client platforms, might look different from the observed reaction on Trad-X. However, given that these markets are traded electronically we would expect participants to arbitrage out any meaningful differences across platforms. Second, our study only captures electronic trading while a large part of the market takes place via voice broking. Future research should aim to consolidate electronic order book data with voice trading activity to further improve our understanding of the modern interest rate swap market.

Notwithstanding the limitations, we demonstrate that robust financial benchmarks can contribute to better financial markets and our model suggests that regulators should bear in mind that clarity for those actors that take part in the benchmark setting process is important. Interventions that make the fixing process noisier would have exactly the opposite effects and would make traders worse off.

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Figures

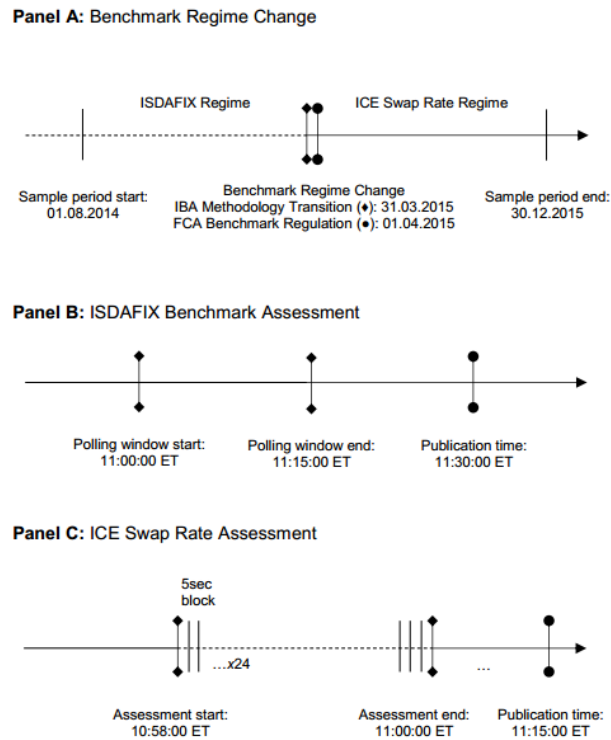


Figure 1. Timeline of Events

Notes: Panel A shows the timeline of events of the benchmark regime change. Our 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 B shows the polling and publication times under the old ISDAFIX regime. Panel C shows the assessment and publication times under the new ICE Swap Rate regime.

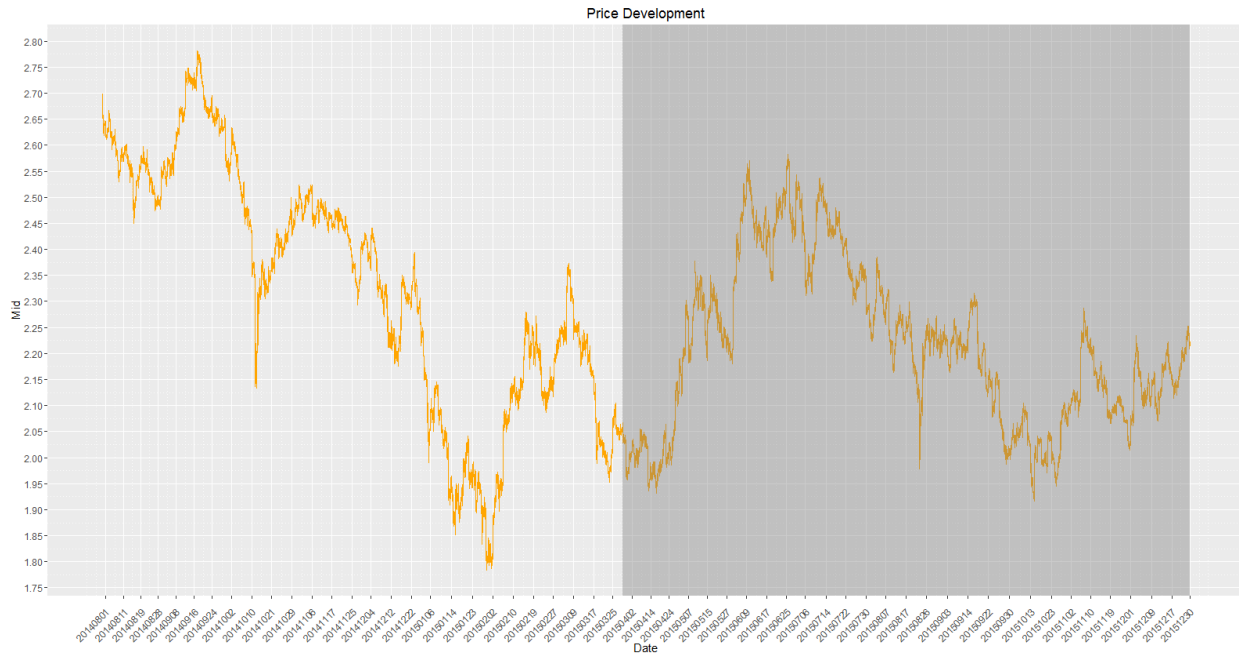


Figure 2. 10Y USD Swap Price Development

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.

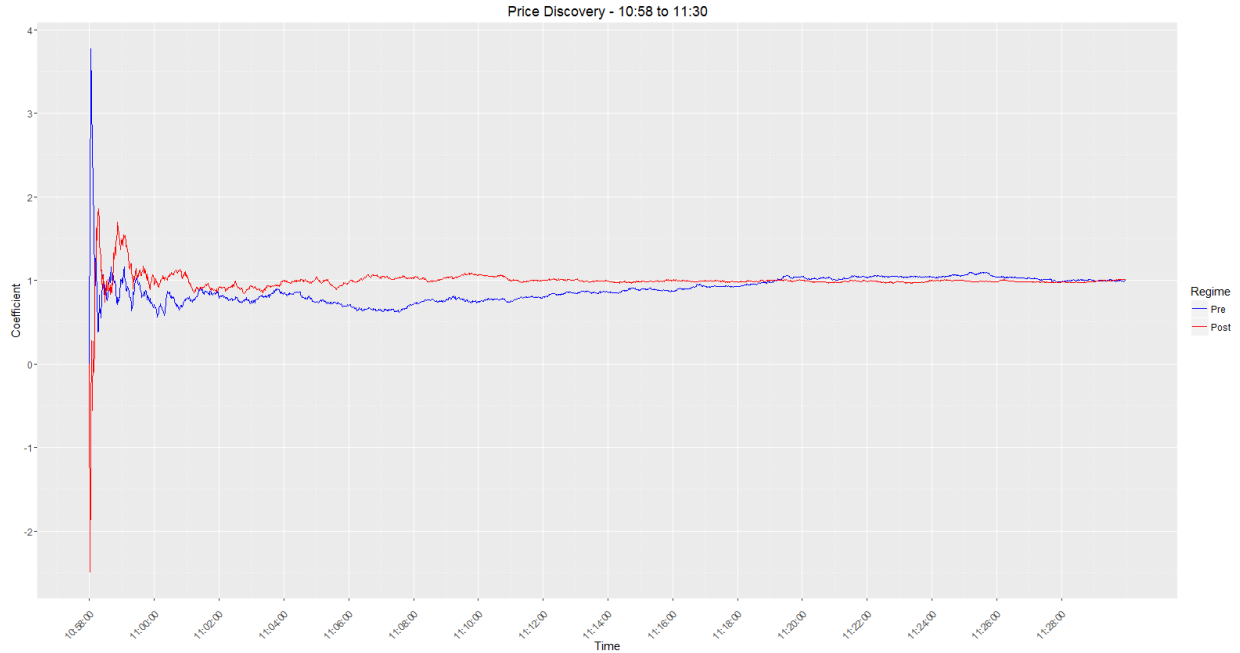


Figure 3. Price Efficiency Around the Benchmark Assessment

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.

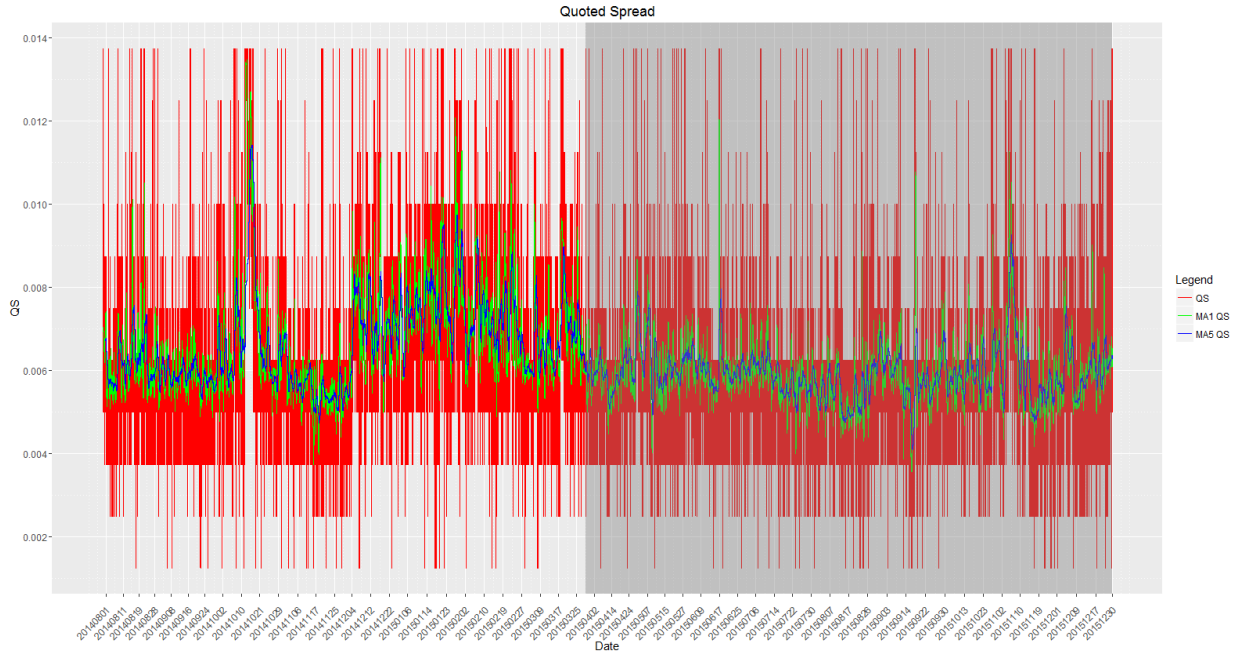


Figure 4. Quoted Spread - 10Y USD Interest Rate Swaps

Notes: This figure depicts the simple quoted spread (red) for the 10Y USD IRS on the Trad-X platform (not time-weighted for illustration purposes) on a second-by-second basis for the trading hours from 9:30am to 4pm ET 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. The green line plots the 1-hour moving average. The blue line plots the 5-hour moving average. Values are expressed in absolute dollar terms.

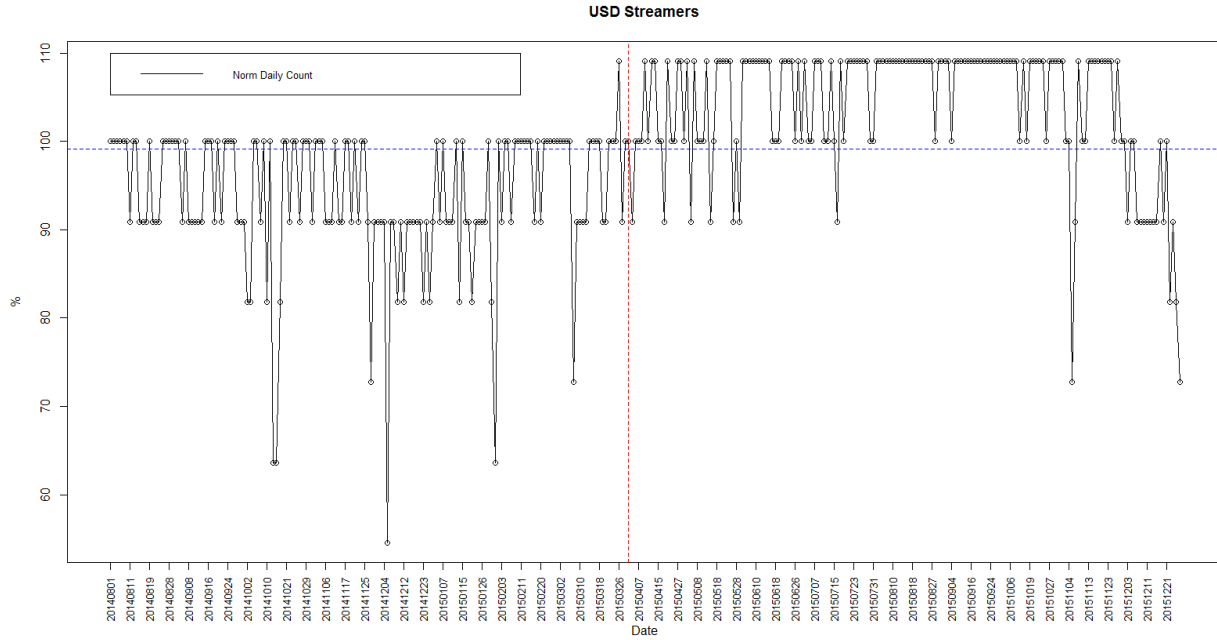
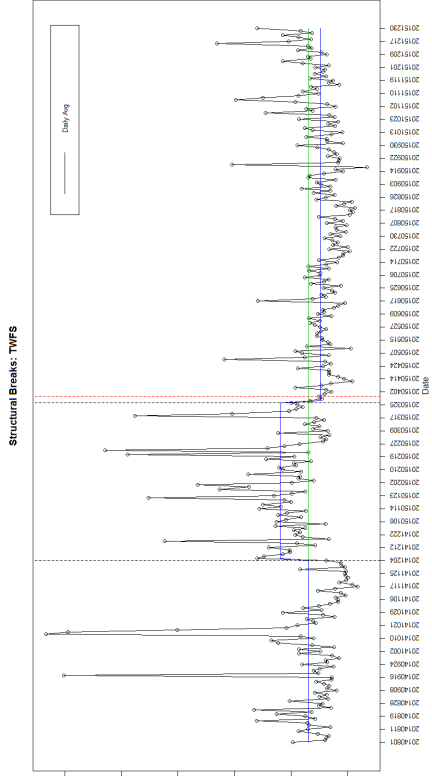
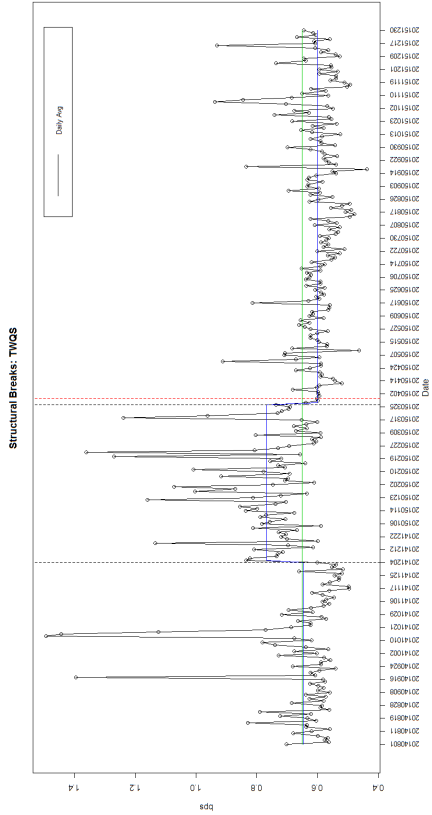


Figure 5. USD Participants

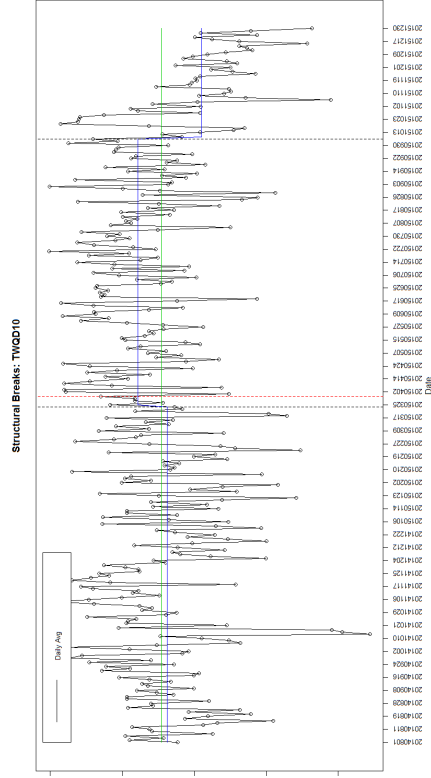
Notes: This figure shows the development of the daily count of USD streamers on the Trad-X platform over the sample period. The numbers are normalized and presented in percentage terms (%). The blue dotted line depicts the long-term average of the time series. The red dotted line marks the event date [$d_0 = 31$ 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].



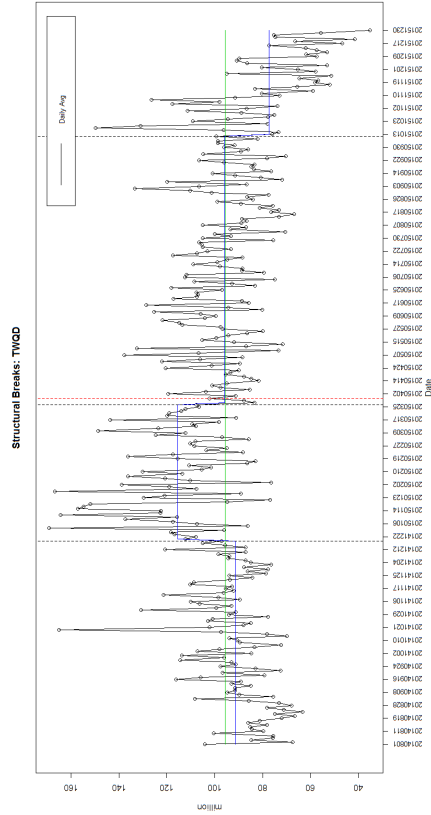
(a) Time-Weighted Quoted Spread



(b) Time-Weighted Fill Spread



(c) Time-Weighted Quoted Depth



(d) Time-Weighted Quoted Depth

Figure 6. Structural Breaks

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 values are expressed in bps (1 bps = 0.01%).

Tables

Table I. Fixed-for-Floating Interest Rate Swaps

Notes: This table shows the tenors (maturity expressed in years [Y]), which are captured by the MAT mandate, and those for which the ICE Benchmark Administration (IBA) is assessing the ICE Swap Rate benchmark. The USD MAT swaps relevant for our 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.

	Currency	Maturity
<i>Made Available to Trade (MAT)</i>	USD	1Y, 2Y, 3Y, 4Y, 5Y, 6Y, 7Y, 10Y, 12Y, 15Y, 20Y, 30Y
<i>ICE Swap Rate Assessment</i>	USD	1Y, 2Y, 3Y, 4Y, 5Y, 6Y, 7Y, 8Y, 9Y, 10Y, 15Y, 20Y, 30Y

Table II. Summary Statistics - Messages

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, cancelations, 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.

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

Table III. Summary Statistics - Transactions

Notes: This table reports descriptive statistics on transactions that were electronically executed 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.

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

Table IV. Benchmark-to-Market Differential

Notes: This table reports the benchmark-to-market differential before and after the change in benchmark regime. We average the $BMD_{t,d}$ over different windows around the 11am 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.

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

Table V. Quoted Liquidity under the ISDAFIX and ICE Swap Rate Regime

Notes: This table reports the long-term comparison of liquidity variables before and after the change in benchmark regime. Time-weighted quoted spread ($TWQS$) reports the spread in absolute dollar terms. Time-weighted relative quoted spread ($TWRQS$) reports the ratio of the quoted spread to the mid-price and is also referred to as %-spread. The time-weighted fill spread ($TWFS$) reports the difference between the hypothetical execution price of a SMS trade on both sides of the book as per the methodology section. Time-weighted quoted depth ($TWQD$) is the sum of the depth at the best bid and offer price. 10-level time-weighted quoted depth ($TWQD10$) is the sum of the depth at the bid and offer side 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. *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.

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

Table VI. Difference-in-Difference Panel Regression for Spread Measures

Notes: This table reports the results of the difference-in-difference (DiD) panel regression model specified in Equation 18 using time-weighted quoted spreads (*TWQS*) and time-weighted fill spreads (*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* * *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.

	TWQS			TWFS		
	(1)	(2)	(1)	(2)	(1)	(2)
<i>Constant</i>	Coeff 6.78E-03	t-Stat 32.82***	Coeff 2.03E-02	t-Stat 9.03***	Coeff 7.35E-03	t-Stat 45.83***
<i>Event</i>	Coeff -6.35E-04	t-Stat -2.85***	Coeff -1.34E-04	t-Stat -0.76	Coeff -2.00E-04	t-Stat -1.1
<i>Treatment</i>	Coeff 2.40E-04	t-Stat 4.24***	Coeff 2.37E-04	t-Stat 4.15***	Coeff 4.89E-04	t-Stat 4.66***
<i>Interaction</i>	Coeff -3.71E-04	t-Stat -4***	Coeff -3.57E-04	t-Stat -3.94***	Coeff -6.80E-04	t-Stat -5.65***
<i>SRVIX</i>			Coeff 1.10E-02	t-Stat 1.26	Coeff 7.07E-03	t-Stat 0.82
<i>TYVIX</i>			Coeff -1.45E-03	t-Stat -0.92	Coeff -2.68E-04	t-Stat -0.19
<i>MESS_10Y</i>			Coeff 4.60E-04	t-Stat 2.38**	Coeff 5.25E-04	t-Stat 2.59***
<i>MESS_12Y:10Y</i>			Coeff -1.25E-04	t-Stat -0.53	Coeff -2.56E-04	t-Stat -1.31
<i>TRANS_10Y</i>			Coeff -6.14E-08	t-Stat -0.01	Coeff 8.80E-06	t-Stat 0.11
<i>TRANS_12Y:10Y</i>			Coeff -2.47E-05	t-Stat -0.42	Coeff -1.45E-05	t-Stat -0.27
<i>PARTICIPANTS</i>			Coeff -2.61E-03	t-Stat -2.74***	Coeff -3.91E-03	t-Stat -3.72***
<i>MACRO</i>			Coeff 4.21E-03	t-Stat 8.78***	Coeff 2.90E-03	t-Stat 6.26***
<i>O:I_10Y</i>			Coeff 1.68E-03	t-Stat 5.2***	Coeff 1.67E-03	t-Stat 5.39***
<i>Adj R²</i>	8.57%	67.28%	6.37%	56.07%		
<i>N</i>	658	637	658	637		
<i>Specification</i>	FE	FE	FE	FE		

Table VII. Short-Term Liquidity Reaction to the Benchmark Regime Change

Notes: This table reports the short-term reaction of liquidity variables around the benchmark regime change. Interval represents the time period, in number of days $d \in D$ before and after the event date [$d_0 = 31$ March 2015], over which the liquidity measures are averaged. Time-weighted quoted spread (*TWQS*) reports the spread in absolute dollar terms. Time-weighted quoted depth (*TWQD*) is the sum of the depth at the best bid and offer price. 10-level time-weighted quoted depth (*TWQD10*) is the sum of the depth at the bid and offer side 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.

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

Appendix A. Data Disclaimer

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

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Appendix B. Carlson and McAfee (1983) proof

First, we can write the expected gain from searching a price than p_i and the expected demand q_i as

$$\sum_{k=1}^{i-1} (p_i - p_k) Pr(p_k) \equiv \frac{1}{n} \left[(i-1)p_i - \sum_{k=1}^{i-1} p_k \right] \quad (\text{B1})$$

$$q_i = \sum_{k=i}^n \frac{1}{k} [G(x_{k+1}) - G(x_k)] \equiv \frac{1}{n} G(x_{n+1}) - \frac{1}{i} G(x_i) + \sum_{k=i+1}^n \frac{1}{k(k-1)} G(x_k) \quad (\text{B2})$$

Second, by induction the following equivalence holds

$$\sum_{k=i+1}^n \frac{1}{k(k-1)} = \frac{n-i}{ni} \quad (\text{B3})$$

Then, from (B2) and the cost distribution (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 a lower price, then using (B1), we obtain

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

Derivation of Δ

Dealers set the price p_i to minimize the penalty Δ . From the quantity equation (4) and the price equation (6), we obtain

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

Dealers know traders expect $p_i = a_i$ and, arranging the previous equation, we obtain

$$\Delta = \frac{v - p_i - snq_i}{F\left(\bar{y} - \frac{\sum_i p_i}{n}\right)} \quad (\text{B4})$$

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 (B4), we finally obtain

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

Derivation of p_i

Traders maximize their utility

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

Using the price equation (6), from the first order conditions we obtain

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

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 (7) becomes

$$p_i = a_i + n \frac{f\left(\bar{y} - \frac{\sum_i a_i}{n}\right)}{f'\left(\bar{y} - \frac{\sum_i a_i}{n}\right)} \quad (\text{B5})$$

To explicit the role of precision in benchmark fixing, define $\zeta \equiv \frac{\bar{y} - \frac{\sum_i a_i}{n}}{\sigma}$, and let $h(\zeta)$ be ζ density function. Then, by changing the variable in (B5), we obtain

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

The model without scaling

We now show how assuming a noisy element for each dealer marginal cost avoids scaling the cost distribution support. Without scaling the distribution, we would have

$$G(x) = \begin{cases} \frac{x}{s} & \text{if } 0 \leq x \leq v \\ \frac{v}{s} & \text{if } x > v \end{cases} \quad (\text{B6})$$

From Appendix B, this distribution would lead to

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

With a noise component for each dealer, $y = \frac{\sum_i a_i + \epsilon_i}{n}$ with $\epsilon_i \sim i.i.d.N(0, \sigma_i^2)$, the price equation would be

$$p_i = a_i + \sum_{j=1}^n \sigma_j \frac{h(\zeta')}{h'(\zeta')}$$

with $\zeta' \equiv \frac{\bar{y} - \frac{\sum_{j=1}^n a_j}{n}}{\sqrt{\sum_{j=1}^n \sigma_j^2/n}}$. Then,

$$q_i = \frac{v + \frac{\sum_{j=1}^n a_j}{n} - a_i + \left(\frac{\sum_{j=1}^n \sigma_j}{n} - \sum_{j=1}^n \sigma_j\right) \frac{h(\zeta)}{h'(\zeta)}}{sn}$$

where $\frac{\sum_{j=1}^n \sigma_j}{n} < \sum_{j=1}^n \sigma_j$, obtaining analogous results as in the case with scaling.

The model without penalty Δ

If no penalty Δ is available, then each dealer i would 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 (4)

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

From the first order conditions we obtain

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

Therefore we need Δ to map the noise in benchmark fixing into the prices.

Also, we have seen that in case 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.

Notes

¹The FCA issued fines amounting to a total of over £2 billion: <https://www.fca.org.uk/markets/benchmarks/enforcement>. It should be noted that the FCA did not issue fines regarding the ISDAFIX benchmark. In the US, the Commodity Futures Trading Commission (CFTC) recently issued and settled multiple charges for attempted manipulation of the ISDAFIX rate. See for example: <http://www.cftc.gov/PressRoom/PressReleases/pr7505-16>, <http://www.cftc.gov/PressRoom/PressReleases/pr7527-17>, <http://www.cftc.gov/PressRoom/PressReleases/pr7371-16>.

²The vast literature on search costs, such as pecuniary and time costs, includes papers such as Duffie, Gârleanu, and Pedersen (2005); Duffie (2012); Zhu (2012); Duffie and Zhu (2016); Flood, Huisman, Koedijk, and Mahieu (1999).

³Streamers are most often dealer banks that continuously "stream" firm quotes to trade interest rate products on regulated electronic trading venues.

⁴A related strand of literature analyzes changes to transparency and competition, often induced by changes to market infrastructure and regulation (see for example Benos et al., 2016; Bessembinder, Maxwell, and Venkataraman, 2013, 2006; Boehmer, Saar, and Yu, 2005; Edwards, Harris, and Piwowar, 2007; Goldstein, Hotchkiss, and Sirri, 2007; Harris and Piwowar, 2006; Trebbi and Xiao, 2016).

⁵This assumption leads to closed-form solutions for the demand curves. It can be relaxed, but it makes the algebra more complex.

⁶We scale the distribution by the average (retail) price p^* to simplify the algebra. The case without scaling is in the appendix.

⁷We are assuming that traders have an incentive to penalize the dealers by exiting the market because in expectations this behavior leads to a lower price. In the appendix, we show that this is equivalent to assuming that traders particularly value the good.

⁸The penalty parameter describes, in a reduced form, the behavior of a repeated game where a trader would cease any activity with the dealer if the realization of the signal is below the threshold, i.e. if he can infer that the dealer is overcharging him, for an analogous structure see Ritter and Taylor (2010).

⁹We report the derivation in the appendix.

¹⁰See statistics of the Bank of International Settlement (<http://stats.bis.org/statx/srs/table/d5.1>) for more details.

¹¹The four electronic trading venues are Trad-X (Tradition), BGC Trader (BGC Partners), i-Swap (ICAP) and tpSWAPDEAL (Tullett Prebon), 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.

¹²MAT is a procedure used to determine if a swap that is required to be cleared is subject to the trade execution requirement and must be traded on SEF using one of the minimum execution methods. As such, a SEF establishes if a swap is made available to trade based on predefined criteria such as availability of buyers and sellers, and trading frequency and volume, and submits the determination to the CFTC for approval. Once certified by the CFTC the MAT swap needs to be traded per trade execution requirement on all SEFs.

¹³Multilateral electronic trading venues for swaps already existed before this date. After the effective date of the mandate SEFs must register with the CFTC and operate under its regulatory oversight.

¹⁴See Benos et al. (2016) and <https://www.clarusft.com/what-is-left-off-sef/>.

¹⁵See <https://web.archive.org/web/20140706105057/http://www2.isda.org/attachment/NjQ10A==/ISDAFIX%20USD%20Rates%2016%20April%202014.pdf>.

¹⁶See <http://ir.theice.com/press/press-releases/all-categories/2015/04-01-2015> for the official press release.

¹⁷The 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.

¹⁸The 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.

¹⁹Data from tpSWAPDEAL (Tullett Prebon), the fourth trading venue, contributes to the assessment of the EUR and GBP ICE Swap Rate.

²⁰The information was gathered mostly from FCA sources and during discussions for this study,

but can also be retrieved from industry sources (for example: <http://www.traditionsef.com/markets/irs/>) or the *SEFView* service of Clarus Financial Technology (<https://sefview.clarusft.com/>). Moreover, the reason that IBA decided to source data from IDBs is based on the fact that prices on these platforms are firm, while some dealer-to-client platforms operate a last look functionality and for this reason some of their prices are not considered to be firm.

²¹Tradition runs a hybrid model offering voice instruction in conjunction with the LOB. We obtained the electronic LOB data for our study. In addition, it is worth noting that Tradition operates two separate order books: one for LCH and one for CME cleared interest rate products. The LCH order book is the more active of the two by a large margin.

²²We exclude holidays following the IBA Holiday Calendar (<https://www.theice.com/iba/holiday-calendars>). Moreover, we exclude days where no benchmark rate was assessed, where an early close of US (or UK) exchanges took place, and where trading took place for less than 50% of the normal trading hours.

²³We refer to swap curve dynamics as the interaction between different swap tenors for example via curve spreads and butterflies. We label as strategies the interaction between the bond and swap market, for example via swap spreads.

²⁴We 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. We still compute the *BMD* based on the few executed transactions and find a qualitatively similar result.

²⁵As reported in the descriptive statistics section, only 165 direct swap trades were executed in the 10Y USD IRS. Further complicating the matter is the fact that of the total 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, not allowing us to calculate effective spread measures for individual swap leg transactions of packaged trades. We nevertheless compute the volume-weighted effective spread (*VWES*) for the few electronically executed direct swap transactions. The mean value for the *VWES* for the pre-BRC period amounts to 0.3 bps and 0.27 bps for the post-BRC period. This corresponds to a reduction of 10%, in line with our results in Table V.

²⁶For robustness, we compute an alternative measure of order book depth simulating the continuous fill of a large transaction (several multiples of the 10Y tenor SMS). We find a highly significant improvement in execution costs for large and very large transactions too. Results can be found in the FCA Occasional Paper 27 and are available on request.

²⁷We only report the results for the spread measures in the main body of the study. The *TWFS* results account for the combined effect on spreads and order book depth and report the net effect. The *TWQD* and *TWQD10* specifications of the DiD panel regressions can be found in the FCA Occasional Paper 27 and are available on request.

²⁸Due to spill over effects caused by the close interaction of the swap curve, the control group is not completely untreated. However, this means that our estimates are conservative. Moreover, differences in characteristics between the tenors are captured by the *Treatment* dummy variable, and we further control for differences in liquidity patterns over time via additional control variables. For robustness purposes, we also run the DiD regressions using multiple tenors where the 5Y and 10Y form the treatment group and the 11Y and 12Y the control group – again chosen based on their liquidity profile. We do not report these results in the main paper because the 11Y tenor is not an 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. In all cases the results are very similar to those reported here.

²⁹The total effect cost savings are computed following the rationale in [Benos, Payne, and Vasios](#), which we adjust to our setting, as: $\sum_{i=1,3} \frac{\beta_i}{100 \times 2} \times Vol_{POST} \times Mat$, where β_i are the coefficients from Equation 18. We 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 b, Table III), and Mat is the maturity of the contract (10 years). For the marginal effect cost savings, we only use the estimated coefficient of the interaction term (β_3). 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} .

³⁰The 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 macroeconomic news announcements, we rerun our 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. Results can be found in the FCA Occasional Paper 27 and are available on request.