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THE CURRENCY THAT CAME IN FROM THE COLD
Capital controls and the information content of order flow

The currency that came in from the cold: Capital controls and the information content of order flow[*]

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Abstract

We analyse how capital controls affect FX microstructure, using as a case study the introduction and subsequent removal of controls in Iceland. We use a VAR of private order flow, Central Bank order flow and EURISK that allows for contemporaneous feedback effects to analyse the impact and information content of trades and find that controls have profound effects. When controls were introduced, volume plummeted, the information content of trading activity declined and became less responsive to macro news. While there was no recovery of trading volume after controls were abolished, the information content and responsiveness of trading activity increased sharply.

Keywords: Exchange rates; Order flow; Market microstructure; Capital controls.
JEL classification: C32; F31; F32; G14; G15.

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1 Introduction

The FX market microstructure literature has had an important role in extending our understanding of exchange rate determination and how the FX market assimilates information. At its core is the idea of information heterogeneity among traders (either because they possess private information not available to other traders or because of different interpretations of publicly available information), so that transaction activity between them plays an important role in aggregating that information into prices – a feature absent in standard macroeconomic models of exchange rate determination.

But what happens to the role of transactions under different market structures? In particular, how does the role of trades and information change under a capital controls regime? In this paper we look at the experience of Iceland's FX market before, during, and after the imposition of capital controls to analyse how both the relationship between trades and the exchange rate and trades and information changes across regimes. Clearly, a case study such as this can only be indicative of broader lessons since, as we shall show in this paper, there are a number of features of Iceland's experience which are unique to Iceland. However, since the issue of empirical microstructure and capital controls have not been directly addressed before we hope this paper can help cast some light on a new question.

To explore these issues we employ the standard identification scheme in a vector autoregression (VAR) model for the Icelandic króna-euro exchange rate and order flow, but with two novel features. First, to account for the fact that we use daily data, we allow for possible *contemporaneous* feedback effects from order flow to exchange rate returns, using an instrumental-variables approach suggested by Daníelsson and Love (2006). Second, we separate the order flow data into private dealer and Central Bank of Iceland order flow, with the latter containing trades were the monetary authority is either a buyer or seller of currency. This allows us to analyse the impact of these two order flow variables on exchange rate returns separately but also to explore the importance of possible additional contemporaneous feedback effects between the two order flow variables.

We find that the introduction of capital controls had dramatic effects on FX market activity. Dealer trading volume plummeted while the impact of an individual trade innovation on exchange rate returns increased significantly. Despite this, a variance decomposition analysis shows a marked decline in the information content of order flow for exchange rate fluctuations. Furthermore, we find limited response of trading activity to macro news (measured using inflation surprises) during the controls period. Once capital controls are

lifted in 2017, we find that the impact of order flow on exchange rate returns increases significantly and that the information content of order flow starts to rise again as order flow becomes more responsive to macro news despite the fact that trading volume remains low.

It turns out that allowing for contemporaneous feedback effects in the VAR analysis plays an important role in identifying the impact of capital controls on the interaction of dealer order flow and exchange rate fluctuations. Their role in understanding the interaction between Central Bank trading activity (which became much more prominent after the introduction of capital controls) and exchange rate returns is even more important. A simple VAR without feedback effects gives the standard positive impact of trade innovations on returns that is broadly stable across the three sub-periods. However, allowing for contemporaneous feedback effects generates complex dynamics between Central Bank trade innovations and exchange rate returns. While the standard direct effect of an order flow innovation on returns is preserved, interactions between dealer and Central Bank trading activity generates an overall negative impact of a Central Bank order flow on returns – possibly reflecting the fact that the Bank had some foreknowledge of an incoming deal order flow in a given day and tried to stifle its impact. Thus, a Central Bank net purchase of Icelandic króna leads to a króna appreciation but this triggers a significant dealer net sale of króna that pushes the exchange rate in the opposite direction, leading to an overall króna depreciation.

The remainder of the paper is organised as follows. Section 2 gives some background on capital controls research whilst Section 3 gives a brief background on the events surrounding the introduction and eventual abolishment of the capital controls. Section 4 describes the structure of the Icelandic FX market. Section 5 contains the core empirical analysis of the paper. Section 6 concludes.

2 The microstructure of capital controls

Understandably perhaps, the analysis of capital controls has tended to focus on their macroeconomic objectives and outcomes rather than their micro impact on the FX market. Thus, most of the literature focuses on two questions: What are the macroeconomic objectives behind the introduction of capital controls? And, how effective are capital controls in achieving those objectives?

In terms of the objectives of capital controls, the earlier literature tended to focus more on monetary policy issues such as exchange rate stability and allowing independent monetary

policy in a regime of fixed exchange rates (Mundell, 1963). The more recent literature has moved on to focus on the market failure which the controls are intended to address and, more broadly, the role of controls in macro-prudential policy (see for example, Rebucci and Ma, 2019).[1] In general, these market failures have come under the headings of pecuniary and demand externalities. Pecuniary externalities, in particular, have become a key focus (e.g. Korinek, 2011) and come about from an over-borrowing problem when market participants do not take into account the impact of their actions on other market participants and how in the face of constraints, financial amplification can lead to crisis. Demand externalities occur in an economy with nominal rigidities and where conventional monetary (and fiscal) policy is constrained (e.g. by the zero lower bound on nominal interest rates, see Korinek and Simsek, 2016). In these circumstances conventional policy cannot optimally respond to shocks so capital controls can play a part. Farhi and Werning (2016) provide a framework where prudential policy, including capital controls, can help address both pecuniary and demand externalities.

Another more recent shift in the capital controls literature has been the move from treating capital controls as a homogenous instrument to a realisation that the categorisation of different types and intensity of controls is important – one of the so-called apples and oranges problems identified by Magud, Reinhart and Rogoff (2011). This literature has focussed on creating more detailed classifications of controls (see for example Chinn and Ito, 2006) though as Fernández et al. (2015) point out these classifications have necessarily been based on de jure categorisation of the form of control and which instruments and flows are subject to those controls.

It is also worth noting that the role of central bank sterilised intervention as part of a capital control regime is also beginning to gain more prominence as central bank trading is often an important part of the FX market under a capital control regime (as it was in the case of Iceland). As Davis et al. (2021) point out there is a clear correlation between capital controls and active intervention by central banks and they argue that this is because intervention allows the impact of controls to be fine-tuned without changing the controls themselves.

Surprisingly perhaps, the burgeoning literature on FX microstructure has barely addressed the issue of capital controls despite the fact that the key route through which capital

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[1] There is also a recent strand of literature that focuses on controls as a method of terms of trade manipulation, see for example Costinot, Lorenzoni and Werning (2014).

controls achieve their objectives is through altering the operation of the FX market. Also, many of the issues highlighted in the capital controls literature have a natural counterpart in the microstructure literature. For example, pecuniary externalities and financial amplification are already beginning to be explored in the FX microstructure literature – most notably in the area of carry trades and carry crashes (see for example Plantin and Shin, 2014, and Breedon, Rime and Vitale, 2016). Issues such as the classification of different types of control and the role of sterilised intervention also have a natural microstructure angle. Thus, one of the objectives of this paper is to begin a discussion of how microstructure can contribute to our understanding of capital controls.

3 The financial crisis in Iceland and the introduction of capital controls

In this section we give a brief overview of economic developments in Iceland both before and after the introduction of capital controls.[2]

3.1 Iceland before the financial crisis

Iceland has a long history of currency volatility, having spent close to a quarter of its post-independence history in currency crisis of some form (see Reinhart and Rogoff, 2011, and Einarsson et al., 2015). The most recent crisis had its roots in the dramatic growth of three Icelandic commercial banks following the privatisation and deregulation of the banking industry in the early 2000's.

All three banks expanded rapidly which, as Fig. 1 shows (from Ólafsson and Pétursson, 2011), resulted in the Icelandic banking system growing to almost 900% of GDP by 2007. This expansion increasingly relied on foreign short-term borrowing resulting in a debt-driven capital inflow surge (cf. Forbes and Warnock, 2012) and a matching expansion of the country's external balance sheet. By the third quarter of 2008, gross external liabilities of the economy had reached 850% of GDP and the net international investment position of the economy had deteriorated to -180% of GDP following a series of large current account deficits leaving Iceland and its banks with significant currency and duration mismatches.

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[2] The section is necessarily concise. For more details on macroeconomic developments leading up to the financial crisis, the crisis itself, and its aftermath, see, for example, Einarsson et al. (2015), Ólafsson (2016), Benediktsdóttir, Eggertsson and Thórarinsson (2017), Jónsson and Sigurgeirsson (2017), Thomsen (2018), and Central Bank of Iceland (2018). A more detailed discussion of the capital controls and the capital account liberalisation can be found in Central Bank of Iceland (2016, 2018) and Ólafsson (2016).
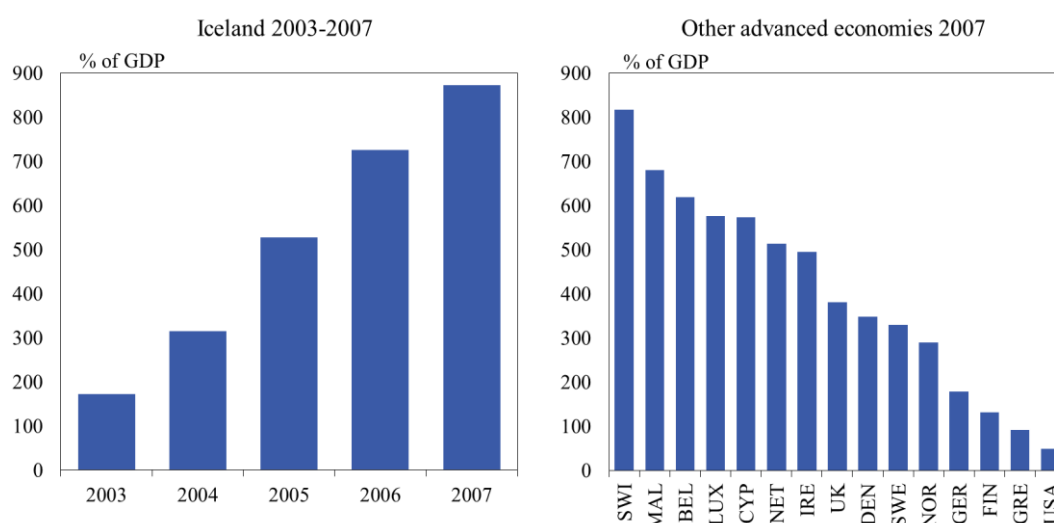
Figure 1 Banking system size in the run-up to the global financial crisis.

The privatisation-driven banking system expansion led to an explosion of credit-fuelled domestic spending. Domestic interest rates rose rapidly and Iceland came to the attention of currency carry traders attracted by a large interest rate differential against other advanced economies. Whilst these disintermediated flows were significantly smaller than those going directly through the banking system, they added to Iceland's overall imbalances.

3.2 The Icelandic financial crisis and capital controls

Following the Lehman Brothers bankruptcy in mid-September 2008, confidence in Iceland's banking system evaporated and within a week in the beginning of October 2008, the three large Icelandic commercial banks collapsed and the Icelandic króna had depreciated by almost 50% against the euro. A severe economic contraction followed, with output contracting by 15% from peak to trough and employment by close to 10%. The sudden stop of access to global funding triggered an even sharper contraction in household spending, which declined by more than 20%.

In an attempt to halt the collapse of the domestic FX market, the Central Bank of Iceland instructed domestic financial institutions to limit currency outflows on 10 October and five days later the Bank attempted to revive trading in the FX market through limited auctions of foreign currency. Eventually it became clear that this was insufficient to halt the capital flight and stabilise the currency. On 28 November, as part of an IMF approved programme, legislation imposing comprehensive restrictions on outward capital movements

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was introduced which blocked all capital outflows, except those related to servicing pre-existing debt obligations and payments of interest income and dividends and payments related to international trade in goods and services.

Additionally, the Icelandic authorities also decided to split the three bank's assets into domestic (managed by domestically active banks) and 'foreign' (legally still domestic entities) which went into resolution rather than the more conventional good bank/bad bank split. In fact, disbursements to foreign creditors were forbidden for balance of payments and supervisory reasons. Whilst these measures effectively froze Iceland's foreign liabilities, they did not remove them. In the case of the banking system, a composition agreement with the failed estates' winding-up boards was reached in February 2016 that included a so-called stabilisation contribution from the estates to the government amounting to almost 20% of GDP. As well as helping to deal with the banking crisis, the capital controls allowed an orderly unwinding of offshore króna positions (so-called carry trades). These became locked inside the country when the capital controls were introduced and amounted to almost 40% of GDP in early 2009. Through a series of auctions held by the Central Bank, they were gradually reduced to roughly 14% by mid-2015. The auctions were a part of a two-sided process where the Central Bank bought foreign currency at a premium from investors willing to lock in their capital investment in Iceland for at least five years and then sold the foreign currency receipts to the holders of the offshore króna, therefore not requiring any drain on the Bank's foreign exchange reserves.

Therefore, by 2016, most of the crisis legacies had been addressed and balance of payment imbalances unwound, making it possible to take the final steps in liberalising the capital account again. In this paper, we assume that this process was completed by 14 March 2017 when most of remaining restrictions were finally removed, including restrictions on capital movements of private households and corporations. The only restrictions remaining applied to the offshore króna holdings, which by March 2017 had declined to less than 8% of GDP.[3] These holdings were eventually released on 4 March 2019 although a relatively large share of those holdings continued to remain in Iceland. It could therefore be argued that the capital controls were not truly abolished until 2019 but for the purposes of this paper we suggest that a more appropriate date to use is two years earlier when restrictions on all new capital movements by all other actors, resident and non-resident alike, were lifted. The timing

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[3] Restrictions on non-hedged derivative trading also remain to this day.

of the post-capital controls era from 2017 is also consistent with the Chinn and Ito (2006) index of financial openness, which rises to its pre-capital controls level in 2017.

4 The Icelandic FX market

4.1 Market structure

Given that Iceland is the smallest country in the world (in terms of population) with its own freely floating currency, the Icelandic FX market is necessarily small. However, as Fig. 2 suggests, FX turnover as a share of GDP is not significantly out of line with other countries. Fig. 2 also shows the dramatic decline in turnover that followed the introduction of controls with turnover falling to about 5% of its pre-controls level. It is noticeable, however, that the lifting of controls in 2017 did not have the same dramatic effect on turnover and post controls turnover remains comparable with that of the controls period.
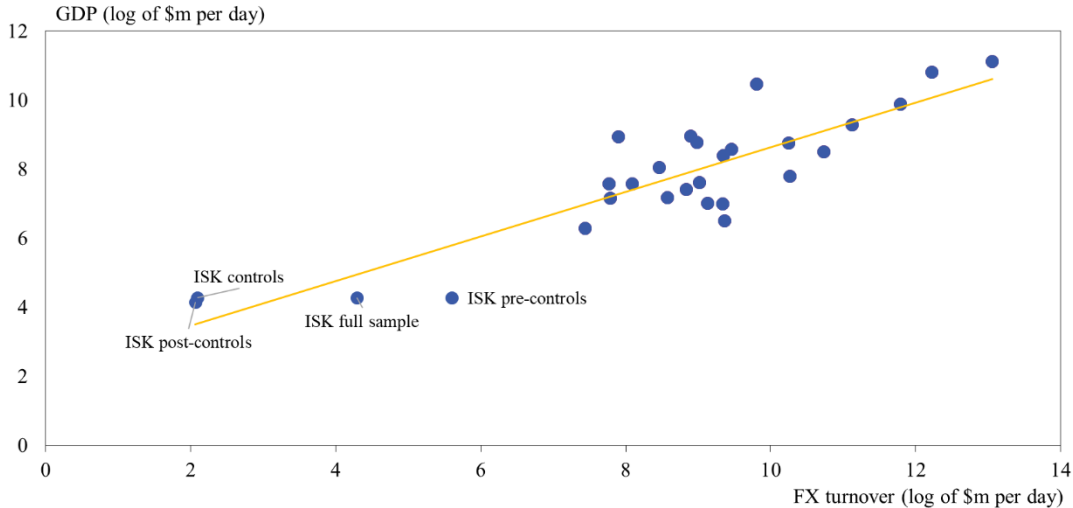
Figure 2 FX market inter-dealer turnover for the ISK and 24 other currencies.[4]

There are only three market makers in the Icelandic FX market (the three domestic commercial banks Arion Banki, Íslandsbanki and Landsbanki – or their previous incarnations). In addition to these three dealers, the Central Bank of Iceland was a key market participant during the controls period (and for a brief period during the currency crisis). For a brief period before their collapse in the currency crisis a decade ago, a few small Savings

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[4] Turnover for other currencies is based on data on inter-dealer turnover from the BIS *Triennial Central Bank Survey of Global Foreign Exchange Market Turnover* surveys (average of surveys between 2007 and 2019).

and Loan institutions also participated in the market as the Central Bank sold them foreign currency directly to ease their foreign currency shortages.

Over our sample, the krona was effectively only directly quoted against the euro (not the US dollar as is conventional in other markets) and standard order sizes fell from 4 million euros prior to the capital control to 1 million euros subsequently.[5] The market structure is such that an individual dealer will typically trade with the other two dealers at the same time, implying that the order flow in the market usually contains information available to all the dealers simultaneously. In the same way, the Central Bank conducts its trades by contacting all the three dealers simultaneously and splitting the order evenly between them.

4.2 The data

We use data from 1 December 2006 (the start of the current market convention of quoting trades in euros) to 24 June 2020 collected by the trading desk of the Central Bank of Iceland. Inspecting the data, however, showed that although the day of the trade was always reliably recorded, the time of within the day was sometimes incorrect – thus leading to an invalid ordering of trades within the day. This precludes any analysis of the tick data and forced us into analysing the data at a daily frequency. Thus, we have a total of 2,676 daily observations of the end-of day EURISK spot exchange rate and order flow cumulated to daily measures (where positive (negative) order flow indicates the net value of purchases (sales) of euros). In addition, we have data on trades involving the Central Bank, both in terms of trades the Bank initiates and trades that are initiated by the counterparty. We are also able to separate Central Bank trades into trades in which the Bank actively tries to move the exchange rate and trades that the Bank pre-announced at regular dates in order to rebuild its foreign exchange reserves without aiming to directly affect the exchange rate (see Section 4.3 for further discussion).

As explained below, the main focus of our analysis are the three sub-samples that mark the capital controls era and the periods before and after their introduction. The dating of the start of the capital controls era is relatively simple: the legislation imposing capital controls was approved in parliament after market closing on 28 November 2008, thus setting

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[5] Although the market switched from quoting trades in US dollars to euros in December 2006, trades were occasionally quoted in other currencies and these trades have been eliminated from our dataset. The total number of trades eliminated for this reason is 141 or just 0.2% of the total of just under 59,000 trades in our sample (almost all are in US dollars, involve the Central Bank, and occur before early 2008). Also excluded is a small number of observations were the spot rate is obviously incorrectly recorded.

the starting date of the capital controls sub-sample as the following trading day, 1 December 2008. The exit date for the capital controls era is not as clear, however, given the stepwise liberalisation of the capital account from 2015. As discussed in Section 3, we assume that the post-capital controls era starts on 14 March 2017 when almost all of the remaining restrictions were finally removed. This implies that the three sub-samples that we use are the pre-capital controls period from 1 December 2006 to 28 November 2008 (487 daily observations), the capital controls period from 1 December 2008 to 13 March 2017 (1,529 daily observations), and the post-capital controls period from 14 March 2017 to 24 June 2020 (660 daily observations).

4.3 Some stylised facts

Table 1 summarises the key statistical properties of the data over our three sub-periods. The pre-controls period is characterised by higher exchange rate volatility and turnover combined with narrower spreads whilst the controls and post controls period have similar volatility and turnover but with wider spreads and a large Central Bank presence in the controls period.[6] The wider spreads in the post-controls period relative to the controls period perhaps reflects the higher information content of trades in the post-controls period as discussed below.

Table 1 Icelandic FX market by regime

Variable	Pre-capital controls period	Capital controls period	Post-capital controls period
Daily volatility (SD of daily returns)	1.17	0.65	0.60
Daily trading volume (millions of EUR)	257.7	9.6	9.6
Average trade size (millions of EUR)	3.4	1.0	1.0
Average effective spread (%)	0.03	0.06	0.11
Central Bank share of turnover (%)	0.3	44.6	9.5
Number of daily observations	487	1,529	660

Table 1 also highlights how the trading behaviour of the Central Bank of Iceland has changed over the sample period, with the Bank becoming much more active in the market following its May 2013 announcement that the Bank intended to use FX market interventions more actively as a policy tool to mitigate exchange rate volatility. This marked a significant change from its pre-crisis view on the usefulness of interventions as an additional policy tool

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[6] Since the precise timing of trades is not known and we have no intraday mid-price estimate, effective spreads are estimated using the regression method employed by Warga (1991) and Schultz (2001). Alternative estimates based on the Abdi and Ranaldo (2017) approach (based on Reuters close, high and low prices) gave similar results over the whole sample but higher spreads in the pre-controls period such that the difference between pre-controls and controls periods spreads was not significant on that measure.

in its inflation-targeting regime (see Pétursson, 2019, for a further discussion) though, as noted above, it is also a common aspect of capital control regimes. This applies especially after 2014 when the Bank actively started leaning against strong appreciation pressures of the króna stemming from a boom in the tourism industry – using the opportunity to boost its foreign reserves at the same time as inflation was below target. The Bank also resumed a programme of buying fixed amount of foreign currency at pre-announced weekly auctions. This programme was ceased in 2017 when these appreciation pressures eased again. As Fig. 3 shows, however, this purchase programme constitutes a relatively small share of the Bank's overall market activity and is dwarfed by the Bank's regular trading in its order flow.
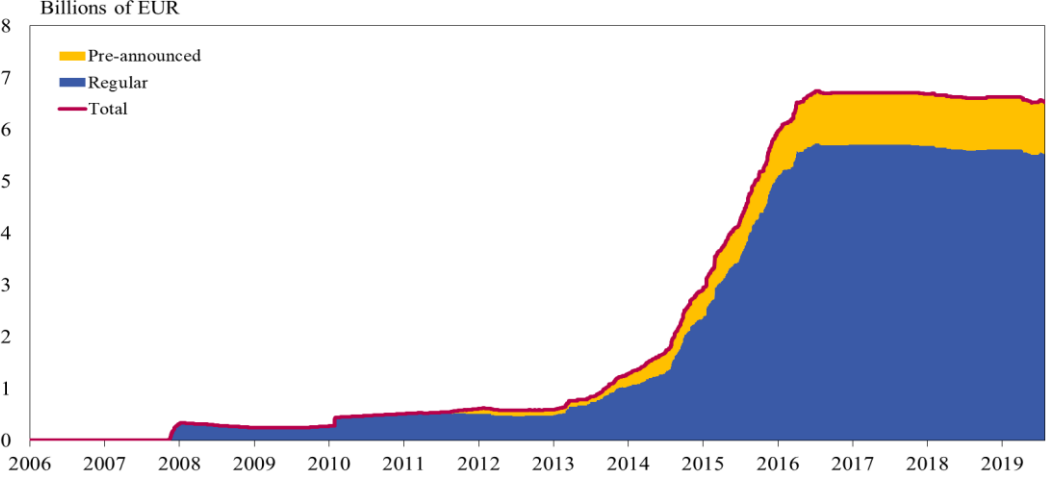
Figure 3 Central Bank cumulative order flow.

4.4 Order flow and exchange rate returns

Table 2 reports the contemporaneous correlation between exchange rate log-returns and different measures of order flow over the whole sample and the three sub-samples. As expected, the correlation between returns and total order flow is positive and statistically significant, but it appears to fall markedly in the capital controls period, before rising to a very high level again in the post-liberalisation period. The relationship between returns and dealer order flow shows a similar pattern, although the correlation does not fall to the same extent in the capital controls period. Its dramatic increase in the post-capital controls period suggests that much smaller trades are currently needed to move the exchange rate compared to the pre-controls period when the market was much deeper and trading volume greater.

Table 2 Contemporaneous correlation of order flow with log-returns

Variable	Whole sample	Pre-capital controls period	Capital controls period	Post-capital controls period
Total order flow	0.286†	0.351†	0.147†	0.882†
Dealer order flow	0.309†	0.349†	0.324†	0.895†
Total Central Bank order flow	-0.091†	0.041	-0.086†	-0.338†
Regular	-0.093†	0.041	-0.091†	-0.342†
Pre-announced	-0.008	–	0.031	-0.040

Note: Dealer order flow refers to trades that do not involve the Central Bank. Central Bank order flow is separated into regular and pre-announced order flow, with the latter designed to build up the Central Bank's foreign reserves with minimum impact on the exchange rate. * (†) denotes that the correlation with log returns is significant at the 5% (1%) critical level.

The relationship between exchange rate returns and order flow involving the Central Bank are strikingly different, however. Total Central Bank order flow is negatively correlated with returns, although that appears restricted to the two latter sub-periods, which is not surprising given that Central Bank trading activity is almost non-existing in the first sub-sample. Distinguishing between regular and pre-announced Bank trades also suggests that the negative correlation stems mainly from the Bank's regular trades while the correlation between returns and pre-announced trades is small and statistically insignificant. This latter finding is not surprising given the fact that these trades are pre-announced and designed so as to have a minimum impact on the spot rate. The negative correlation between the Bank's regular trades and returns might appear troubling at first sight. However, as we show below, this appears to reflect a complex interaction between dealer and Central Bank order flow – highlighting the need for a structural analysis, such as the one we embark on in the next section, to fully understand the dynamic relationship between exchange rate returns and order flow. The different relationship between returns and order flow across the three sub-samples in addition highlights the need to analyse this dynamic relationship across these three sub-samples.

Finally, Fig. 4 further highlights the importance of distinguishing between dealer and Central Bank order flow. Looking only at total order flow would suggest a breakdown of the relationship between cumulative order flow and the exchange rate after 2015 when the Central Bank embarks on its programme to buy foreign currency to boost its foreign reserves. However, focusing only on dealer activity preserves the standard positive relationship between the exchange rate and cumulative order flow – which has become even stronger in the post-capital controls period as discussed earlier.[7]

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[7] Killeen, Lyons and Moore (2006) report a similar breakdown in the relationship between cumulative order flow and exchange rates in the run up to the introduction of the euro in the late 1990s, although in our case this reflects the trading activity of the Central Bank.

The figure also shows that Central Bank order flow has been much larger than dealer order flow in recent years and how most of the order flow imbalances in the FX market stem from Central Bank transactions. Thus, private dealers systematically de-cumulated euros over the capital controls period, which the Central Bank absorbed into its foreign reserves.[8] The figure shows, however, that the market has largely been in balance in the post-capital controls period since 2017.
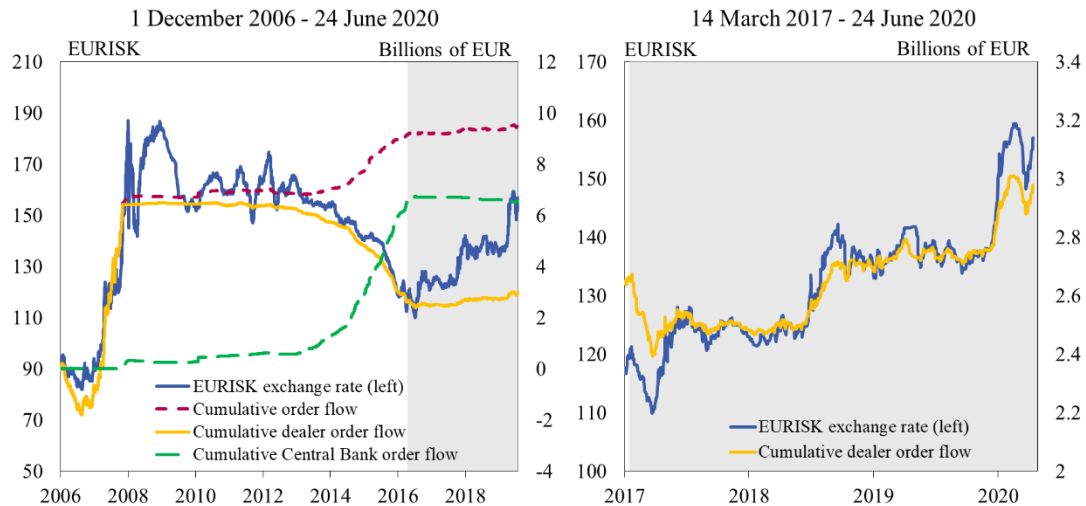

Figure 4 Spot exchange rate and cumulative order flow. Dealer order flow refers to order flow not involving the Central Bank. The shaded area in the left panel depicts the post-capital controls period from 14 March 2017, highlighted in the right panel.

5 Empirical analysis

5.1 The VAR model

To investigate the relationship between trading activity and FX returns more closely, we estimate a vector autoregression (VAR) model that has become a core tool for analysing complex economic interactions and dynamics since Sims (1980) and was first introduced to the microstructure literature by Hasbrouck (1991) to analyse the information content of order flow in the US stock market. The VAR approach has since become standard in the microstructure literature, with recent applications to the FX market including Evans (2002), Payne (2003) and Daníelsson and Love (2006).

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[8] Our analysis below focuses on aggregate dealer trading behaviour as we are not able to report any results on individual trader properties without risking revealing the identity of the three large dealers. What the individual dealer data does reveal, however, is that while the overall trading volume and intensity is very similar across all three dealers, the aggregate dealer de-cumulation of euros shown in Fig. 4 is only due to two of them, while the third has in fact increased its euros inventory over the sample period. The latter property most likely reflects the different client base of each of the three banks.

The VAR approach and the challenges we face in our particular exercise can be summarised as follows. First, note that for any stationary $n \times 1$ vector stochastic process, $\boldsymbol{x}_t$, there exists an infinite vector moving average (VMA) representation of the data given as:

$$(1) \qquad \boldsymbol{x}_t = \boldsymbol{C}(L)\boldsymbol{u}_t$$

where $\boldsymbol{C}(L)$ is a $n \times n$ polynomial in the lag operator, $L^s \boldsymbol{x}_t = \boldsymbol{x}_{t-s}$, given as $\boldsymbol{I} + \boldsymbol{C}_1 L + \boldsymbol{C}_2 L^2 + \cdots$, and $\boldsymbol{u}_t$ is a $n \times 1$ vector of one-step-ahead linear forecast errors in $\boldsymbol{x}_t$ with a $n \times n$ variance-covariance matrix $E(\boldsymbol{u}_t \boldsymbol{u}_t') = \boldsymbol{\Sigma}$. The VMA representation can always be transformed into a finite-order VAR of the following form:

$$(2) \qquad \boldsymbol{x}_t = \boldsymbol{A}(L)\boldsymbol{x}_t + \boldsymbol{u}_t$$

where $\boldsymbol{A}(L) = \boldsymbol{I} - \boldsymbol{C}(L)^{-1}$ is a $n \times n$ lag polynomial of order p, given as $\boldsymbol{A}_1 L + \boldsymbol{A}_2 L^2 + \cdots + \boldsymbol{A}_p L^p$. Note that Eq. (2) is a reduced-form relation and no structural interpretation of the $\boldsymbol{u}_t$ innovations is therefore possible. What is of interest are the set of structural relations leading to this reduced form. These are given by the structural form of the VAR:

$$(3) \qquad \boldsymbol{A}_0 \boldsymbol{x}_t = \boldsymbol{B}(L)\boldsymbol{x}_t + \boldsymbol{\epsilon}_t$$

where $\boldsymbol{B}(L) = \boldsymbol{A}_0 \boldsymbol{A}(L)$ and $\boldsymbol{\epsilon}_t = \boldsymbol{A}_0 \boldsymbol{u}_t$ are the $n \times 1$ structural innovations with a diagonal variance-covariance matrix $\boldsymbol{\Omega}$ given as $\boldsymbol{\Omega} = \boldsymbol{A}_0 \boldsymbol{\Sigma} \boldsymbol{A}_0'$. $\boldsymbol{A}_0$ thus allows for a mapping from the VAR forecast errors $\boldsymbol{u}_t$ to the structural innovations $\boldsymbol{\epsilon}_t$, but a sufficient number of restrictions need to be imposed on $\boldsymbol{A}_0$ for those structural innovations to be identified. Note, that there are $n(n+1)$ parameters in $\boldsymbol{A}_0$ and $\boldsymbol{\Omega}$ to be estimated, whereas there are only $n(n+1)/2$ parameters in $\boldsymbol{\Sigma}$. We can reduce this number by normalising the diagonal of $\boldsymbol{A}_0$ to unity but we are still left with $n(n-1)/2$ restrictions that need to be imposed on $\boldsymbol{A}_0$ to identify the structural innovations.

In our case, $\boldsymbol{x}_t$ is the 2×1 vector, $\boldsymbol{x}_t = (r_t, y_t)'$ where r_t is log-returns and y_t is order flow.[9] Thus, we need to impose one further restriction on $\boldsymbol{A}_0$ to identify the two

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[9] As discussed below, we extend our analysis to split y_t into dealer and Central Bank order flow but to simplify the exposition, we only focus on aggregate order flow here but all the results easily generalise. We also ignore deterministic variables, such as a constant, to simplify the exposition.

structural innovations. This comes naturally from the microstructure literature, which suggests that trades logically precede price changes in tick-by-tick data, i.e. that order flow contemporaneously affects log-returns but not vice versa (e.g. Payne, 2003). In this case A_0 becomes an upper-triangular matrix:

$$(4) \qquad A_0 = \begin{pmatrix} 1 & -\beta \\ 0 & 1 \end{pmatrix}$$

with β giving the contemporaneous impact of order flow on log-returns. The structural innovation to the return equation, ϵ_t^r, can then be interpreted as reflecting the impact of public information on returns, while the structural innovation to the order flow equation, ϵ_t^y, represents unpredictable transaction activity and hence the impact of dealers' private information on returns through their trading activity (see e.g. Payne, 2003).[10] Thus, the greater the contribution of order flow innovations to the total variation of exchange rate returns, the greater the information content of trading activity.

This causal ordering can of course be recognised as the familiar Choleski factorisation often used to identify structural VAR models and is typically used in the microstructure literature. However, as shown by Daníelsson and Love (2006), this recursive ordering really becomes untenable for data sampled at lower frequencies than a few seconds. For lower frequencies, such as the daily data we use, it seems plausible that traders can respond to intra-day price changes and trade on that information before the end of the day (i.e. within the sampled frequency used). In this case, a trade innovation will cause an intra-day movement in the exchange rate but this will feed back again into order flow over the same time interval, for example reflecting expectations of other traders that the original trade innovation will cause further trading activity that will lead to price movements within that period. This would imply that the Choleski factorisation is not sufficient to identify the structural innovations, with A_0 now becoming:

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[10] The key premise of the microstructure literature is that market transactions convey information that is not common knowledge. Thus, order flow innovations move exchange rates because of informational asymmetries (Glosten and Milgrom, 1985). An alternative theoretical argument for the causal relationship between order flow and returns is based on inventory control arguments (Lyons, 1995). Note that private information in this context can also include public information (e.g. macro news) that individual traders interpret, and react to, differently (cf. Evans, 2002, and Evans and Lyons, 2008).

$$(5) \qquad \boldsymbol{A}_0 = \begin{pmatrix} 1 & -\beta \\ -\delta & 1 \end{pmatrix}$$

and δ representing the contemporaneous impact of log-returns on order flow. If this contemporaneous feedback effect is positive (i.e. if $\delta > 0$), it is easy to show that a standard VAR with no feedback effects will underestimate the trade impact on returns, i.e. that the no-feedback VAR will underestimate the impact of order flow on exchange rate returns. Thus, a positive order flow innovation leads to a price increase, which in turn leads to a further increase in order flow in the same period pushing prices even further and it is this second-round effect that the standard Choleski factorisation of the VAR fails to account for. The feedback effect can of course also be negative (i.e. $\delta < 0$), for example if an initial order flow innovation leads to a negative order flow as other traders expect the exchange rate to reverse within the trading day. The point is: ignoring these feedback effects can lead to a large and significant bias in the estimation of the impact of trade innovation on returns in microstructure models using data sampled at relatively low frequencies.[11]

As a solution to the identification problem posed by the contemporaneous feedback trading effect, Daníelsson and Love (2006) propose using instrumental variables to estimate the VAR, replacing the endogenous log-returns and order flow with suitable instruments.[12] To explain, stack the T observations of r_t and y_t into $T \times 1$ vectors $\boldsymbol{R}$ and $\boldsymbol{Y}$, respectively. Furthermore, specify the $T \times (1 + k)$ matrix $\boldsymbol{Z}_r$ which contains the $k = 1 + 2p$ regressors on the right-hand side of the return equation in the structural VAR in Eq. (3), i.e. the contemporaneous value of y_t and the lags of r_t and y_t. A corresponding $T \times (1 + k)$ matrix $\boldsymbol{Z}_y$, containing the contemporaneous value of r_t and the lags of r_t and y_t, is specified for the order flow equation. This allows us to re-write the structural VAR in a stacked form:

$$(6) \qquad \begin{pmatrix} \boldsymbol{R} \\ \boldsymbol{Y} \end{pmatrix} = \begin{pmatrix} \boldsymbol{Z}_r \boldsymbol{\pi}_r \\ \boldsymbol{Z}_y \boldsymbol{\pi}_y \end{pmatrix} + \begin{pmatrix} \boldsymbol{\epsilon}_r \\ \boldsymbol{\epsilon}_y \end{pmatrix}$$

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[11] As discussed in Daníelsson and Love (2006), the contemporaneous effects of returns on order flow can arise for other reasons than the feedback trading effects referred to here. For example, it could reflect the fact that traders may want to break large orders into a number of smaller trades to be executed over a short time interval – which will show up as order flow being contemporaneously affected by returns in the data.

[12] An alternative way to estimate the structural VAR with contemporaneous feedback effects would be to assume that there are different exogenously given volatility regimes were the variation in the regime-depending variance-covariance matrix is used to identify the regime-invariant parameters in $\boldsymbol{A}_0$ (see Rigobon, 2003). However, it is not clear whether this approach would work here as our results suggest that $\boldsymbol{A}_0$ in fact varies over the three sub-samples we analyse.

where ϵ_r and ϵ_y are the $T \times 1$ vectors of the structural innovations and π_r and π_y are the corresponding $(1 + k) \times 1$ vectors of coefficients in the structural VAR (the coefficients of A_0 and $B(L)$). As the regressors in the Z_r and Z_y matrices contain endogenous variables (the contemporaneous values of y_t and r_t, respectively), the two equations need to be estimated with instrumental variables. Once adequate instruments for the endogenous variables are identified we can apply a standard 2SLS procedure to estimate the coefficients in the structural VAR in Eq. (6). From this we can then derive impulse responses in the standard way using the VMA representation in of the structural VAR:

(7) $x_t = \Psi(L)\epsilon_t$

where $\Psi(L) = A_0^{-1}(I - A(L))^{-1}$ is an $n \times n$ infinite order lag polynomial containing the marginal impact of unit changes to the structural innovations in ϵ_t.

5.2 Extending the VAR to incorporate two order flow variables

In our empirical analysis below we split the order flow variable into dealer (i.e. non-Central Bank) order flow, y_t^d, and Central Bank order flow, y_t^c.[13] The x_t data vector is therefore a 3×1 vector $x_t = (r_t, y_t^d, y_t^c)' = (r_t, y_t)'$ with A_0 now becoming:

(8) $A_0 = \begin{pmatrix} 1 & -\beta_d & -\beta_c \\ -\delta_d & 1 & -\gamma \\ -\delta_c & -\phi & 1 \end{pmatrix}$

where β_d (β_c) represents the contemporaneous impact of a dealer (Central Bank) trade innovation on returns and δ_d (δ_c) the contemporaneous feedback impact from returns to dealer (Central Bank) order flow. Separating total order flow into dealer and Central Bank

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[13] We also tried separating the Central Bank order flow variable further into regular and pre-announced order flow (see the discussion in Section 4). We find that the estimated impact of dealer order flow innovations on log-returns is practically identical to that reported in the main text while the impact of regular Central Bank order flow is very similar to the aggregate Central Bank order flow (which is dominated by the regular order flow, cf. Fig. 3) reported here. Thus, not only does a more granular measure of the Central Bank order flow fail to add anything to our analysis, it also sacrifices any comparison of results with the pre-capital controls period as there are no pre-announced Central Bank trades in that sub-period, thus precluding estimation of the VAR for that sub-period.

order flow also allows for possible contemporaneous interaction effects from the order flow of one type of trader to the other, captured by γ and ϕ.

In this case the VMA representation of the structural VAR in Eq. (7) becomes:

$$(9) \qquad \begin{pmatrix} r_t \\ \boldsymbol{y}_t \end{pmatrix} = \begin{pmatrix} \psi_{11}(L) & \boldsymbol{\psi}_{12}(L) \\ \boldsymbol{\psi}_{21}(L) & \boldsymbol{\Psi}_{22}(L) \end{pmatrix} \begin{pmatrix} \epsilon_t^r \\ \boldsymbol{\epsilon}_t^y \end{pmatrix}; \qquad \boldsymbol{\Omega} = \begin{pmatrix} \sigma_r^2 & 0 \\ 0 & \boldsymbol{\Omega}_y \end{pmatrix}$$

where $\boldsymbol{y}_t = (y_t^d, y_t^c)'$ and $\boldsymbol{\epsilon}_t^y = (\epsilon_t^d, \epsilon_t^c)'$. $\boldsymbol{\psi}_{12}(L)$ and $\boldsymbol{\psi}_{21}(L)$ are 1×2 and 2×1 vectors respectively, and $\boldsymbol{\Psi}_{22}(L)$ and $\boldsymbol{\Omega}_y$ are 2×2 matrices.

In the following section, we use these impulse response functions to analyse the impact of order flow innovations on EURISK log-returns over the three non-overlapping sub-samples discussed in the previous section. We estimate the VAR with Newey-West heteroscedasticity and autocorrelation consistent standard errors and construct confidence bands around the impulse responses using bootstrapping methods. First, however, we need to find suitable instruments for our three endogenous variables.

5.3 The choice of instruments

The key challenge to using the instrumental variables approach suggested by Daníelsson and Love (2006) is to find suitable instruments to add to the VAR, i.e. variables that correlate with our endogenous variables but, at the same time, can be treated as exogenous in the estimation process. In their analysis of the EURUSD exchange rate, Daníelsson and Love (2006) suggest using lagged values of the GBPUSD and EURGBP exchange rates as instruments. This draws on a number of studies showing the importance of cross-effects of order flow in one currency on exchange rates in other markets (see, e.g., Evans and Lyons, 2002). For our choice of instruments, we also look to the fact that the Icelandic FX market is small and relatively isolated, i.e. there is very limited international trading participation in the market. But, ultimately, we let the data speak on the validity of our choice of instruments.

The first set of instruments we propose using are contemporaneous and lagged values of the credit default swap (CDS) on Icelandic government bonds. The CDS is a contract where the seller of the CDS promises to compensate the buyer in the event of default by the underlying issuer, in this case the Icelandic government. Trading in CDS contracts is quoted in US dollars and is completely separated from trading in the Icelandic FX market and, to a

great extent, by a completely different set of traders, which would suggest that the CDS can serve as an instrument in our analysis.

The second set of instruments we propose using are contemporaneous and lagged values of log-returns of the EURUSD exchange rate. As Daníelsson and Love (2006) point out, using contemporaneous values of their currency crosses as instruments can lead to an incorrect inference as all currency crosses are simultaneously determined in fully integrated global FX markets and cannot therefore be treated as exogenous to one another. In our case, however, there are two key arguments that suggest contemporaneous EURUSD could be a valid instrument. First, trades in the Icelandic FX market are all quoted in terms of the EURISK rate and no active USDISK market exists. Therefore, triangular arbitrage between EURUSD, EURISK and USDISK cannot occur. Second, given the small size of the Icelandic economy and its FX market, it seems unlikely that movements in the Icelandic króna influence the EURUSD rate. It therefore appears plausible that any correlation between the EURISK and EURUSD rates is not driven by events in Iceland and that we can safely use the contemporaneous EURUSD rate as an instrument.

In addition to the CDS and EURUSD log-returns, the first-stage regressions also include 10 lags of EURISK log-returns and the two order flow variables, thus effectively adding them to the list of instruments. Table 3 summarises the key properties of our first-step regression analysis.[14] First, we see that a C-test for instrument validity suggests that our proposed instruments work quite well across all three sub-periods. The least successful attempt to find instruments for our three endogenous variables is in the two latter sub-periods for the Central Bank order flow equation (although the CDS is found to be close to being accepted by the C-test in the capital controls period). For the other two equations (and the Central Bank order flow equation in the pre-capital controls period), the C-test strongly rejects the over-identifying restriction that the CDS and EURUSD log-returns are invalid instruments. The lower panel of Table 3 also show that R^2 is quite high in most cases, suggesting that our list of instruments does a decent job in explaining the variation in the three endogenous variables.

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[14] Note that there are fewer effective observations for estimating the VAR due to a few missing observations for the CDS, mostly at the very start of the sample period.

Table 3 Instrumenting exchange rate returns and order flow

	Pre-capital controls period	Capital controls period	Post-capital controls period
	C-test (p-values)		
Return equation	0.000	0.000	0.002
Dealer order flow equation	0.000	0.014	0.002
Central Bank order flow equation	0.000	0.487	0.234
	Coefficient of multiple determination		
Return equation	0.535	0.264	0.154
Dealer order flow equation	0.244	0.313	0.152
Central Bank order flow equation	0.876	0.214	0.214
Number of observations	341	1,509	646

Note: The upper panel of the table reports a Wald test for the joint validity of CDS and EURUSD log-returns as instruments for EURISK log-returns and order flow based on Newey-West heteroscedasticity and autocorrelation consistent standard errors. The regressions include contemporaneous values and 10 lags of the CDS spread and the EURUSD exchange rate plus 10 lags of log-returns and the two order flow variables. The lower panel reports R^2 values for the instrumental regressions.

5.4 Adding contemporaneous feedback effects to the VAR

In the second-step of our analysis, we replace the three original endogenous regressors with their instrumented values and proceed to estimate the structural VAR with contemporaneous feedback effects using the standard OLS approach to each equation of the VAR. We use the Schwartz information criterion to choose the lag length of the VAR. This leads us to choose 4 lags for the VAR in the pre-capital controls period but 1 lag in the two other sub-periods.

We start by reporting the estimated parameters of the A_0 matrix in Eq. (8), which gives the direct contemporaneous impact for each of our three endogenous variables to the three structural innovations. As shown in Table 4, the direct impact of dealer order flow on log-returns (β_d) is positive as suggested by the microstructure literature. The impact effect is highly significant and markedly higher in the latter two sub-periods than in the pre-capital controls period. The slope coefficient for Central Bank trades (β_c) is found to be insignificant in the first sub-period, which is not surprising given the very small number of Bank trades in that period. In the latter two sub-samples, however, the coefficient is found to be positive and highly significant – with a point estimate of about a half the size of that for dealer trades. Overall, we therefore obtain the positive contemporaneous effects of order flow on returns as predicted by the microstructure literature.

The table also shows that the direct feedback effect of log-returns on dealer order flow (δ_d) is both positive and highly significant across the three sub-periods. The same applies for the direct feedback effect from returns to Central Bank order flow (δ_c), again except in the first sub-period. Finally, the table shows that the direct feedback effects between the two

order flow variables (γ and ϕ) are negative and highly significant, again except in the pre-capital controls period. Thus, the data suggest that a positive dealer (Central Bank) trade innovation leads to a contemporaneous negative Central Bank (dealer) order flow response. The point estimates suggest that these effects are non-trivial: for example, a one million euros Central Bank purchase typically generates a sale of roughly half a million euros within the same trading day and similar feedback effects are found from dealer order flow innovations to Central Bank trading activity in the last two sub-periods. As we see in Section 5.4.2, these order flow feedback effects generate complex interactions between the three structural innovations over time – dynamics that would not be captured in a lower-dimensional VAR that does not allow for these contemporaneous feedback effects.

Table 4 Estimates of contemporaneous impact effects in VAR with feedback effects

	Pre-capital controls period	*Capital controls period*	*Post-capital controls period*
Return equation			
Impact of dealer order flow (β_d)	0.00010 (4.38)	0.00091 (4.73)	0.00071 (15.31)
Impact of Central Bank order flow (β_c)	-0.00050 (-0.79)	0.00047 (3.51)	0.00040 (4.11)
Dealer order flow equation			
Impact of log-returns (δ_d)	3959.990 (3.77)	212.945 (2.72)	1142.080 (13.98)
Impact of Central Bank order flow (γ)	0.221692 (0.08)	-0.53734 (-13.87)	-0.66685 (-6.67)
Central Bank order flow equation			
Impact of log-returns (δ_c)	-74.415 (-0.91)	305.136 (2.45)	668.824 (3.41)
Impact of dealer order flow (ϕ)	0.00085 (0.12)	-1.49868 (-15.62)	-0.69164 (3.83)

Note: Estimates of contemporaneous impact effects in the A_0 matrix in Eq. (8). Order flow is measured in millions of euros. *t*-values reported in brackets are based on Newey-West heteroscedasticity and autocorrelation consistent standard errors.

Table 5 summarises other key features of the structural VAR. First, we see that the explanatory power of the structural VAR is high in most cases, even reaching more than 80% for both the returns and dealer order flow equations in the post-capital controls period.[15] Interestingly, the quality of fit does not appear to deteriorate markedly compared to a no-feedback VAR (not reported but available upon request) even though actual values of the three endogenous variables have been replaced by their instrumented values – reflecting the importance of the contemporaneous feedback effects allowed in the VAR with feedback effects. The table also reports Wald exclusion tests for each equation. Of particular interest here is the high significance of order flow for log-returns. We also find strong dynamic effects

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[15] Note that R^2 becomes negative for the return equation in the capital controls period. This reflects the fact that the actual values of the endogenous variables are used rather than their instrumented values to construct the regression residuals when calculating the R^2. This means that the residual sum of squares is no longer constrained to be smaller than the total sum of squares and R^2 can therefore be negative.

from returns to order flow and between the two order flow variables, except in the pre-capital controls period where the Central Bank order flow appears independent of log-returns and dealer order flow. But again we must note the relatively small number of Central Bank trades in this sub-period.

Table 5 Summary of VAR with contemporaneous feedback effects

	Pre-capital controls period	*Capital controls period*	*Post-capital controls period*
	Return equation		
Coefficient of multiple determination	0.315	-0.245	0.844
Exclusion test for dealer order flow (*p*-values)	0.000	0.000	0.000
Exclusion test for Central Bank order flow (*p*-values)	0.076	0.000	0.000
	Dealer order flow equation		
Coefficient of multiple determination	0.181	0.372	0.874
Exclusion test for log-returns (*p*-values)	0.002	0.013	0.000
Exclusion test for Central Bank order flow (*p*-values)	0.118	0.000	0.000
	Central Bank order flow equation		
Coefficient of multiple determination	0.680	0.274	0.414
Exclusion test for log-returns (*p*-values)	0.709	0.019	0.002
Exclusion test for dealer order flow (*p*-values)	0.764	0.000	0.001
	Information content of order flow		
Percentage of overall variability explained by order flow	0.725	0.569	0.901
	VAR lag order and number of observations		
VAR lag order (Schwartz information criteria)	4	1	1
Number of observations	341	1,509	646

Note: For individual equations of the VAR, the table reports R^2 values from the second-step regression of the VAR and *p*-values of a Wald exclusion test for each equation based on Newey-West heteroscedasticity and autocorrelation consistent standard errors. The information content of order flow is defined as the share of total variability of spot rate returns explained by order flow variation, σ_{wy}/σ_w^2, from Eq. (10).

Finally, Table 5 reports the proportion of overall volatility of log-returns explained by order flow. This variance decomposition can be obtained from the VMA in Eq. (9) and gives a direct measure of the relative importance of informed trades in determining spot rate movements (see Hasbrouck, 1991). To do this, note that the permanent effect of a unit returns innovation is given as $\psi_{11}(1)\epsilon_t^r = \left(1 + \sum_{i=1}^{\infty} \psi_{11,i}\right)\epsilon_t^r$ and the permanent effect of a trade innovation as $\boldsymbol{\psi}_{12}(1)\epsilon_t^y = \sum_{i=0}^{\infty} \boldsymbol{\psi}_{12,i}\,\epsilon_t^y$. Under the assumption that spot exchange rates can be decomposed into a random walk and a stationary component, the total volatility of the permanent component of the spot rate can therefore be expressed as:

(10) $\quad \sigma_w^2 = \psi_{11}(1)^2 \sigma_r^2 + \boldsymbol{\psi}_{12}(1)\boldsymbol{\Omega}_y\boldsymbol{\psi}_{12}(1)' = \sigma_{wr} + \sigma_{wy}$

Total volatility in the permanent component of the spot rate can therefore be decomposed into the contribution of public (σ_{wr}) and private (σ_{wy}) information and the importance of private information-based trades in determining the spot rate can be measured as σ_{wy}/σ_w^2. Table 5 shows that a large portion of the total variation in log-returns is due to the long-run impact of private (or asymmetric) information contained in order flow. The contribution of private information falls from roughly three-fourths in the pre-capital controls period to just above half in the capital controls period, before rising again to 90% in the post-capital controls period. For comparison, Payne (2003) finds that around 40% of the variation in the USDDEM exchange rate is driven by variation in order flow.

5.4.1 Impulse responses for dealer trade innovations

The final part of our VAR analysis looks at the dynamic effects of a trade innovation on exchange rate returns using impulse responses from the VMA representation of the structural VAR in Eq. (9). We start by looking at the effects of dealer order flow innovations, while the next section analyses the effects of Central Bank trades. We use bootstrapping methods (see, e.g. Hamilton, 1994) and report the median and the 16th and 84th percentiles of the distribution (i.e. a one standard deviation band) computed from 1,000 bootstrap replications. Fig. 5 shows the impact of a 1 million euros dealer order flow innovation on EURISK log-returns over a twenty-day period (i.e. a four-week trading period) estimated over the three sub-samples. For comparison, we also report the median impulse responses from a corresponding no-feedback VAR calculated in an identical way. The identification of the trade innovation in the no-feedback case is based on the Choleski factorisation, ordering dealer trades before Central Bank trades.

Overall, the results from the feedback VAR suggests that a dealer trade innovation has large, positive, and highly significant effects on log-returns. In the pre-capital controls period, a 1 million euros dealer purchase causes the króna to depreciate by ½ basis point during the day of the trade and roughly 2 basis points permanently. The impact becomes larger in the capital controls period, when a similar dealer purchase of euros causes the króna to depreciate by 5 basis points during the trading day and permanently by close to 11 basis points. The impact rises even further in the post-capital controls period, with the contemporaneous impact rising to 52 basis points and the permanent effect to roughly 65 basis points. The results therefore suggest that the impact of trade innovations on log-returns has risen substantially over the three sub-periods. The adjustment of the spot rate to a trade

innovation has also become more rapid: it takes roughly a week for 90% of the permanent effect to be realised in returns in the first sub-period but prices have more or less fully adjusted the day after the trade innovation in the last sub-period.
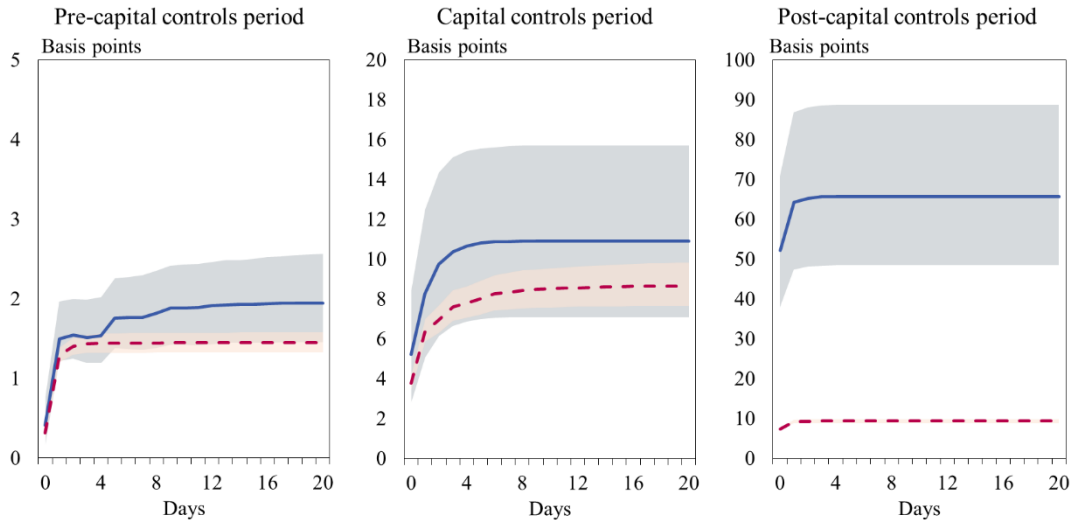

Figure 5 Impulse response functions of the spot rate to a dealer trade innovation of 1 million euros from a VAR with contemporaneous feedback effects. The solid line is the median of the distribution using 1,000 bootstrap replications while the dark shaded area gives a one standard deviation band, i.e. the range between the 16th and 84th percentiles of the distribution. The broken line and the light shaded area show the corresponding median impulse response and one standard deviation band for the no-feedback VAR.

The marked increase in the permanent effect of a trade innovation on returns over the three sub-periods coincides with a significant decline in market volume and activity in the two second sub-periods compared to the pre-capital controls period as discussed in Section 4. This is consistent with the empirical findings in Lyons (1996) and Payne (2003) and the theoretical microstructure model of Admati and Pfleiderer (1988). This can also explain why we find significantly larger permanent effects of order flow in the two latter sub-periods, when market volume is particularly low, than typically found in other much more liquid FX markets (e.g. Payne, 2003, and Daníelsson and Love, 2006).

The above results therefore suggest that the permanent effect of trade innovations on returns rose significantly during the capital controls period, in which market volume declined dramatically from the pre-capital controls period. However, the variance decomposition of information content of order flow in Table 5 suggests that the aggregate contribution of transaction activity to permanent spot rate movements actually falls during this period. Combined, the results therefore suggest that although the impact of trade innovations on returns rose as market volume declined, the trading process actually became less informative,

presumably as it became more reflective of inventory rebalancing than exploitation of private information. This changes once restrictions on capital mobility were lifted again: although market volume remains low, the impact of trade innovations rises even further and the information content of order flow rises again and becomes very large (we discuss this in more detail below).

Finally, Fig. 5 compares the impulse responses attained from the feedback VAR to the simple no-feedback one. Two features of the no-feedback VAR stand out. First, the estimated impulse responses are smaller (but remain statistically significant from zero) compared to those obtained from the feedback VAR, particularly in the post-capital controls period. The no-feedback VAR suggests that a 1 million euros dealer trade raises log-returns by about 1½ basis points in the pre-capital controls period, increasing to 8-10 basis points in the two latter sub-periods. Thus, just as in Daníelsson and Love (2006), we find that the contemporaneous feedback effect is economically important across the three sub-periods (with the difference between the two impulse responses statistically significant in the last period) and that the no-feedback VAR underestimates the impact of dealer trade innovations on log-returns.

Second, although we do observe a similar rise in the permanent effect of trade innovations in the capital controls period, the dramatic increase in the post-capital controls period we find in the feedback VAR is absent in the no-feedback VAR. This suggests that the increased permanent effect of trade innovations on log-returns in the post-capital controls period can be attributed to a greater intensity of feedback effects. Thus, it appears that a given dealer trade triggers a much stronger reaction from other dealers in the post-capital controls period than in the more voluminous pre-capital controls period.[16]

A final feature of the no-feedback VAR worth highlighting is the fact that it shows an even more pronounced decline in the portion of the total variation in log-returns explained by order flow during the capital controls era than the feedback VAR. The variance-decomposition gives very similar estimates of σ_{wy}/σ_w^2 for the pre- and post-capital controls periods to those reported in Table 5 but the share of total returns variation explained by order flow declines to 37% in the capital controls period compared to 57% for the feedback VAR.

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[16] According to the feedback VAR, the permanent effect of a dealer order flow innovation rises from 1.9 basis points in the pre-capital controls period to 65.7 basis points in the post-capital controls period, or by 63.8 basis points. The corresponding increase according to the no-feedback VAR is only 7.9 basis points. Thus, the contribution of the feedback effect to the total increase in the permanent order flow effect between the pre- and post-capital controls periods is 55.9 basis points (the difference between 63.8 and 7.9 basis points) or close to 90%.

5.4.2 Impulse responses for Central Bank trade innovations

Fig. 6 reports the impulse responses for Central Bank trade innovations over the three sub-periods. First, note that the no-feedback VAR impulse responses display the typical positive and statistically significant impact of order flow innovations across all the three sub-periods. The exchange rate tends to appreciate by 1 to 4 basis points during the intervention day, with the impact rising further over the following days. The biggest long-term impact is found in the pre-capital controls period, consistent with the findings in Dominguez (2003) that interventions tend to have larger effect when they coincide with greater market activity. But the confidence band is large, which is not surprising given the lack of Central Bank trading activity in that period. The estimates for the two latter sub-periods are tighter, suggesting a long-term impact of 2 basis points in the capital controls period, rising to 5 basis points in the post-controls period.
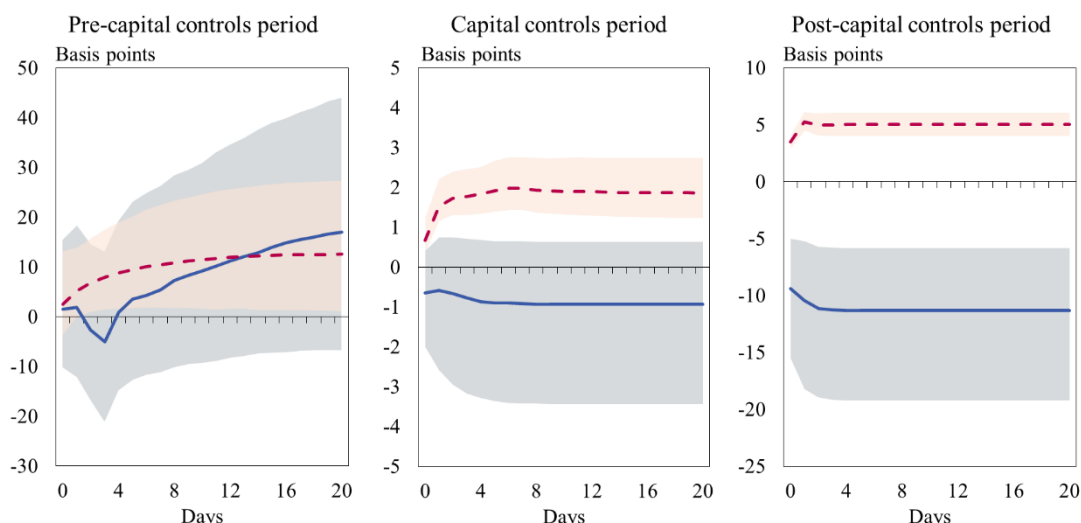

Figure 6 Impulse response functions of the spot rate to a Central Bank trade innovation of 1 million euros from a VAR with contemporaneous feedback effects. The solid line is the median of the distribution using 1,000 bootstrap replications while the dark shaded area gives a one standard deviation band, i.e. the range between the 16th and 84th percentiles of the distribution. The broken line and the light shaded area show the corresponding median impulse response and one standard deviation band for the no-feedback VAR.

The feedback VAR gives very similar results for Central Bank interventions in the pre-controls period, although the confidence bands are wide enough to make them insignificant from zero. However, for the latter two periods, the dynamic effects are drastically different from what we find for the no-feedback VAR. Now, the impulse responses turn negative – albeit only significantly so in the post-capital controls period.

26

Comparison with results from the no-feedback VAR suggests that this comes about as Central Bank trading triggers dealer trading (remember the negative coefficients γ and ϕ in Table 4) that is sufficiently strong to reverse the sign of the impulse responses reported in Fig. 6. For example, when the Central Bank enters the market to sell króna and buy euros, the positive β_c from Table 4 implies an initial euro appreciation against the króna. However, this triggers an immediate additional sell-off of euros from the dealers and this inter-dealer rebalancing effect is sufficiently strong to reverse the initial euro appreciation and leave the euro lower against the króna by the end of the trading day.

This finding is particularly striking given the fact that the estimated impact effects of Central Bank order flow innovations in the A_0 matrix in Table 4 are found to be significantly positive – suggesting that we have successfully identified the Central Bank order flow innovations. There are a number of possible explanations for this result, but a plausible one is that the Central Bank had some foreknowledge of dealer order flow in a given day and tended to trade in order to stifle its impact. Of course, this effect makes the interpretation of the structural Central Bank trade innovations more challenging.

5.5 Order flow, macro news and capital controls

A key finding of the VAR analysis in the previous section is that the price impact of dealer order flow increased once capital controls were introduced as FX market liquidity plummeted. At the same time our variance decomposition results in Table 5 suggest that the information content of order flow innovations actually declined following the introduction of capital controls. Once the capital account is liberalised again, however, order flow becomes more informative and the impact of trade innovations on log-returns rose even further.

One potential explanation for why order flow became less informative once capital controls were introduced is that trading activity became less responsive to macro news once capital movements became restricted. This would be consistent with a key finding from the microstructure literature on exchange rate determination, which argues that order flow is an important channel through which macro news impact the exchange rate (cf. Evans and Lyons, 2008, Love and Payne, 2008, and Rime, Sarno and Sojli, 2010).[17]

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[17] This stands in contrast to the standard rational expectations models of exchange rate determination, which argue that publicly available information (such as macro news) should directly be incorporated into exchange rates without any need for trading activity.

To test whether the declining information content of order flow in the capital controls era reflects reduced impact of macro news on trading activity, we look at the relationship between order flow and inflation surprises. This is the only macro variable for which surveys of market expectations are available for the whole sample period – but it should also be the single most important macro variable for an inflation-targeting central bank such as the Central Bank of Iceland. The inflation surprises are at a monthly frequency (collected by the Central Bank) and are measured as the deviation of financial institutions' median expectations of the month-on-month change in the CPI just prior to its official release (positive values therefore indicate that monthly inflation was higher than expected). Corresponding monthly observations of order flow are constructed by cumulating the daily order flow for each month. The CPI data release is in the last week of each month and the surveys shortly before, so order flow cumulated over each month should give a sufficiently close measure of trading activity leading up to each data release. For this analysis, we only use dealer order flow as we are focusing on the impact of macro surprises to the market on trading behaviour.

Fig. 7 shows scatter plots of inflation surprises and monthly order flow over the three sub-samples. The scatter plots display a negative relationship between inflation surprises and order flow, suggesting that higher-than-expected inflation triggers a negative order flow, i.e. a net selling of euros, which our previous analysis suggests would lead to an appreciation of the króna relative to the euro. This increased demand for króna presumably reflects market expectations of a monetary tightening following a higher-than-expected inflation reading, which would be consistent with a monetary policy reaction function of an inflation-targeting central bank, such as the Icelandic one (cf. Engel, Mark and West, 2008). This is also consistent with the findings from Love and Payne (2008) and Rime, Sarno and Sojli (2010) for other inflation-targeting central banks. Macro news appear to explain about 3% of the total variation in order flow in the pre-capital controls period. This is similar to what Rime, Sarno and Sojli (2010) find for the USDJPY exchange rate but somewhat lower than for the EURUSD and GBPUSD rates – probably reflecting the much broader set of measures of macro news they use (see also Dominguez and Panthaki, 2006, and Love and Payne, 2008).[18]

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[18] We exclude November 2008 from our pre-capital controls sample as the FX market had already stopped functioning (see the discussion in Section 3), making it impossible for traders to react to macro surprises in that month. Including the November observation, reduces the correlation between inflation surprises and order flow somewhat but not sufficiently to alter the results reported in the main text. Note also that there are two large outliers that may appear to be dominating the results in the pre-capital controls era: a large order flow in March 2008 and a large inflation surprise in the following month. However, excluding them only serves to strengthen
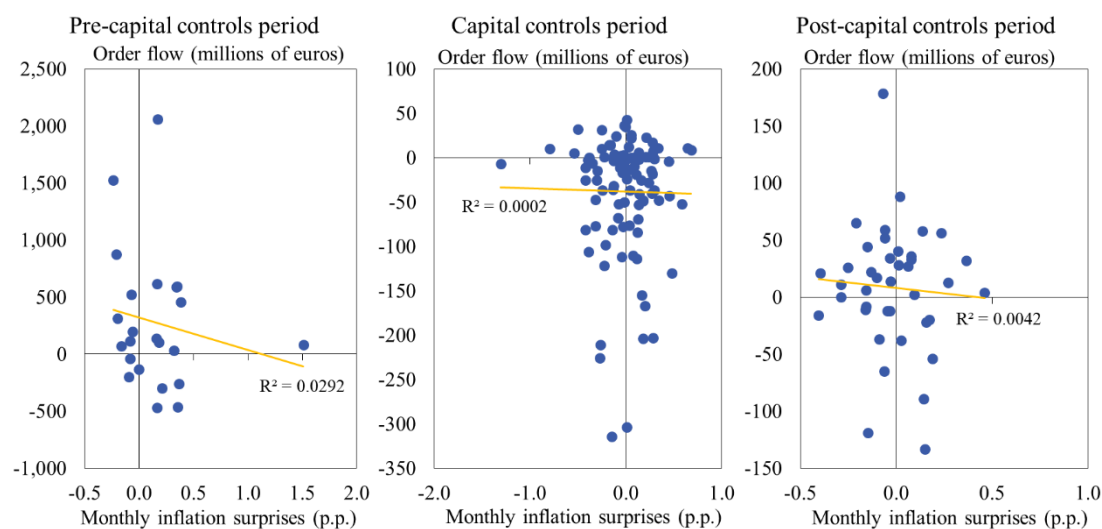
Figure 7 Order flow and inflation surprises over the three sub-samples.

However, the relationship between inflation surprises and order flow appears to weaken considerably once capital controls are introduced in late 2008, with R^2 falling to just 0.02%, before rising again once the capital controls are abolished in 2017. Although our analysis only includes one measure of macro news (albeit an important one) and the number of observations available is small – in particular in the pre- and post-capital controls periods – these scatter plots do suggest that order flow became less responsive to macro news during the capital controls period. This tentatively suggests that an important reason for the decline in the information content of order flow during the capital controls period was that FX market traders reacted less to macro surprises than they did before. The reaction of trades to macro news strengthens again after the capital account is liberalised, although the relationship between order flow and macro news remains weaker than in the pre-capital controls period.[19]

6 Conclusions

This paper analyses how capital controls affect the microstructure of the FX market, using as testing ground the introduction of capital controls in Iceland in November 2008 and their

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the results: R^2 increases to 4% when the inflation surprise is excluded, to 5% when the order flow observation is excluded, and 11% when both are excluded.

[19] We also looked at monthly unemployment surprises using an ARMA(2,2) model estimated using a rolling window to generate one-step-ahead forecasts. We find a positive correlation between unemployment forecast surprises and order flow (and thus a króna-euro depreciation), with R^2 almost five times higher during the pre-capital controls period than in the controls period, that almost doubles again once the capital controls are lifted. These results are available upon request.

eventual lifting more than eight years later. As the first empirical paper to analyse capital controls from a microstructure perspective we have focussed on a standard microstructure question – the information content of trades. However, even with this somewhat limited question we find some strong results, particularly when comparing the capital controls and post-capital control periods which – on the face of it – look rather similar. The dramatic rise in both the information content of trades and the link between macro news and trading once controls are removed, even though total trading volume was unchanged, indicate that the capital controls regime had fundamental effects on information transmission in the FX market.

Overall, we hope that this first tentative step into the empirical microstructure of capital controls will be the beginning of a new approach as so many questions concerning controls that have traditionally been analysed at a macro level could, arguably, be illuminated by the microstructure perspective. These range from the mechanics of sudden stops and pecuniary externalities that are the problem capital controls are designed to solve to a detailed analysis of all the different measures (including greater Central Bank involvement in the FX market) that come under the broad heading of capital controls to establish the role of each.

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