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TRADING WITH THE INFORMED AND AGAINST THE UNINFORMED: FLOWS AND POSITIONING IN THE GLOBAL CURRENCY MARKET

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FX trade settlement data from CLS provides the most comprehensive view of the opaque market of OTC currency trades. We use the flows of investment funds and non-financial corporates and develop trading signals where the former reflects speculative strategies, while the latter trade for liquidity needs. The implication is we trade in the direction of the funds flows and trade against large corporate flows, which should be followed by price reversals. Trading with informed flows yields positive risk-adjusted performance. Incorporating the liquidity trades signal improves risk-adjusted performance and greatly lowers the tail risk of the model.

1 Introduction

Among the major financial asset classes, the currency market is unique in terms of the low transparency of trading activity. There is no central exchange and exchange-traded currency futures and options activity is quite small relative to the overall size of the market. The large and opaque character of over-the-counter (OTC) currency trading results in an inability to know how much trading there is in each currency each day except for the snapshot provided by the BIS Triennial Survey. Investors holding risky positions in currencies would benefit from information regarding currency flows and the market's positioning in assessing returns and risk from their positions. Our goal in this paper is to utilize the most comprehensive data source for currency-trading activity, CLS, and simulate trading strategies where flows and positioning information inform portfolio decisions.

Researchers have used various sources of FX flow data in the past. Publicly available sources include the BIS Triennial Survey, which is only available every 3 years and so is of limited use for real-time investment strategies, and exchange-traded

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futures and options data, which is a small fraction of the OTC trade volume. Some researchers have obtained proprietary data. Such data include FX order flow of individual banks and trades of FX electronic brokerages. Section 2 reviews alternative data sets that have been used to proxy for currency market flows and positioning and discusses the potential advantages of CLS data relative to the alternatives.

The CLS data contain all trades settled on the platform. There are more than 25,000 entities clearing their FX trades through CLS. The data are disaggregated into the end-user categories of corporates; nonbank financial institutions; and funds. We utilize the CLS clearing trades to proxy for FX flows and positioning. This is the most comprehensive data available outside of the BIS Triennial Survey. Section 3 reviews the CLS data and provides a visualization of CLS flows and positioning over time. A comparison is made with exchange-traded futures and options to demonstrate how different the FX flows are as measured by CLS compared to exchange-traded instruments.

We assume that FX investment fund flows are "smart money" and trade with a view toward profiting from future exchange rate changes. We construct a trade strategy that trades in the direction of the funds trades. We further assume that corporate flows are motivated by liquidity needs and are not driven by a view toward future exchange rate changes. Since a large corporate flow may have a short-term price impact, our trade strategy trades against large flows of corporates, betting on reversal. As a risk control, we construct a proxy for positioning in each currency as the cumulated flow. When positioning is exceptionally large, we reduce our exposure to that currency in order to limit the risk of market-wide correlated trades associated with position unwinding. Section 4 constructs and backtests investment portfolios using this strategy. We first simulate an intraday trading strategy and find that trade costs offset any alpha gain, so we turn to a daily strategy and find supportive backtest results of alpha associated with trading the CLS flows.

Section 5 develops optimized portfolios, starting with a generic momentum signal. Then we add the flows variables using a Black-Litterman framework for blending the generic momentum strategy with the views offered from funds and corporate flows. We find that the flows add value over the generic strategy. Funds flows yielded very good performance early in the sample and then performance leveled off. The addition of the corporate flows signal enhanced the consistency of the risk-adjusted performance and also improved tail-risk management substantially.

Finally, Section 6 offers a summary and conclusions.

2 Currency Positioning Data

Practitioners and academic researchers have used various measures of currency flow and positioning data, and the quality of the data has likely improved over time. A brief overview of alternative data sources includes those listed below.

2.1 BIS Triennial survey

The BIS Triennial Survey gives the most comprehensive view of FX market activity.[1] Every 3 years in April, the Bank for International Settlements surveys the world's central banks, who survey their domestic banks, in order to report daily trading activity across all currencies and instruments. While the BIS data are global and comprehensive, they are only available once every 3 years, so are of limited use for currency investing in real time.

2.2 Exchange-traded futures and options

The CFTC in the US provides a publicly available resource known as the Commitment of Traders report that reports positioning in exchange-traded futures and options on several currencies. The data reflect positioning on each Tuesday and are released to the public the following Friday. While the volume traded is small relative to OTC currency activity, the availability of the data results in market participants and scholars often utilizing the data as a proxy for market positioning.[2]

2.3 Single-bank flow data

Some researchers have utilized FX trade data from market-maker banks.[3] These data are proprietary and not shared with the research community. Banks generally standardize the data and do not provide raw volume data in order to conceal the true size of their trading volume. In addition, each bank has idiosyncratic features in that they have different clienteles, they aggregate the data differently across client segments, and typically do not differentiate between trades done electronically, algorithmically, or by voice. An interesting variant in this area is the flow and positioning data of custodian banks, like State Street. State Street data record transactions of the institutional investors for whom they serve as custodian.[4] These data are trades of end-users of FX and are conceptually different than brokerage platforms that often include much interbank trading.

2.4 Electronic brokerage data

The FX market traditionally had two major platforms for interbank trading: Reuters Matching and EBS. Many researchers have used data from these sources.[5] As discussed in Moore *et al.* (2016), the data from these sources are a relatively small and shrinking part of the market. However, the visibility to market participants makes the central limit order books useful references for price discovery. While the price data are considered representative, there is a lack of volume data so that researchers sometimes use the number of buys and sells by the trade aggressor as a proxy for trade flow.

Beyond the specific types of data just discussed, some researchers have inferred positioning or flow from price changes or other approaches. One interesting approach by Pojarliev and Levich (2011) was to estimate factor loadings on currency investment styles (like carry or momentum) across currency funds and define "style crowdedness" as the percentage of funds with significant positive exposure to a given style less the percentage with a significant negative exposure.

2.5 CLS data

CLS is the leading provider of FX settlement services and sits at the center of the currency-trading universe. CLS membership includes more than 70 of the world's most important financial institutions. In addition, there are more than 25,000 third-party clients using the service. CLS members issue payment instructions from trades arising from electronic systems or voice. On the average day they settle around USD5 trillion of payments. Since the launch of CLS in 2002, systemic risk in the FX market has been greatly reduced by the multilateral netting and settlement that occurs via the CLS network. Given the widespread use of CLS for settling currency trades globally, this gives CLS a rich data set containing the history of all trades settled on the system. The CLS FX Order Flow report provides FX spot order flow data aggregated into useful categories like market makers and price takers, and trades of nonbank financial institutions with banks, funds with banks and corporates with banks.

Given the depth of transactions covered, the CLS data may be the best single source for capturing a global view of FX trade volume. The data capture different venues and participant types and there is no regional or market-segment bias. Only recently have the data been available to researchers and only a few papers have used the data.[6] These data may give the best possible view of trade flows and positioning available to researchers and investors at a frequency that can be implemented in a trading strategy. While we work with a historical data set, the data are available in real-time to investors via a subscription from CLS. The next section presents the CLS data used in this paper and discusses important features of the data.

3 CLS Positioning Data

CLS compiles data into three end-user categories: corporates, nonbank financial institutions, and funds. Institutions in these categories are viewed as consumers of liquidity or price takers and their bank counterparties are market makers. We aggregate the trade data for each day for each category to create a daily flow data set.

3.1 Daily flows

For analysis, we argue that data on fund trades with banks is most useful for currency investors, as funds trade financial assets with a view toward profits from changes in exchange rates. Corporate and nonbank financial institution trades are more likely driven by liquidity motives rather than FX investing motives. We will compare the three different types of flows to reveal what differences exist. For each day, we measure the net trade flow in two ways: first, the value of buys minus sells in units of the base currency; second, the number of buy transactions minus the number of sell transactions. We later will create a positioning proxy variable by the cumulative sum of the net daily flows.

Figure 1 illustrates the flows for EURUSD trading. The three types of flows have quite different patterns. Fund flows are larger and more volatile on a daily basis than corporations or nonbank financials. Nonbank financial flows are generally much smaller than EUR1 billion per day, with only a few outlier days of much larger size. Similarly, corporate flows are also generally smaller than EUR1 billion per day until 2016, when recurring spikes of EUR purchases occur at fairly regular intervals. This is suggestive of calendar-based trading. Additional illustrations of currency flows are found in the Appendix. Appendix Figure A.1 for GBPUSD is generally similar to EURUSD in that the daily fund flows tend to be larger and more volatile than corporate or nonbank financial flows. Interestingly, the nonbank financial flows had large GBP sales spiking in 2013 at recurring points in time. These negative GBP spikes show up again in 2017 and persist through the end of the sample. Figure A.2 for USDJPY shows daily fund flows that are larger than corporate or nonbank financial flows. Interestingly, toward the end of the sample, there are relatively frequent episodes of large USD sales for corporate and nonbank financials but not for the fund flows.

The episodes of relatively large trades at fairly regular calendar dates by corporate and nonbank financials are reflective of their greater propensity for liquidity-oriented trading than funds. We suspect that the information content of fund flows should be greater than that of corporates or nonbank financials.[7] Digging deeper into trade flows of funds, we computed the average daily trade size over the sample for each currency pair. Summary statistics are presented in Table 1. Note that the mean average daily trade size ranges from USD 4,783,720 for USDCAD trades to USD 1,111,143 for USDILS trades. It is well known that EURUSD has much larger total trading volume than any other currency pair, but Table 1 reports statistics for the total amount traded divided by the number of trades each day denominated in the base currency settled by CLS. The largest average trade size on a single day

Figure 1 EURUSD daily flows.

Table 1 Average trade size for funds.

Currency Pair	Mean	Maximum	Minimum
EURUSD	4,422,533	53,012,885	572,023
GBPUSD	2,049,605	38,043,969	57,384
USDJPY	3,455,456	28,901,055	81,736
USDCAD	4,783,720	88,569,543	2,876
USDCHF	2,430,335	27,591,873	27,052
USDDKK	2,477,472	163,900,952	1,978
USDHKD	1,116,649	18,540,629	67,466
USDILS	1,111,143	34,582,132	55
USDMXN	1,927,775	29,352,232	12,643
USDNOK	1,590,312	40,376,098	2,405
USDSEK	2,182,414	69,005,332	6,221
USDSGD	1,207,076	20,944,415	55
USDZAR	1,647,871	24,890,662	9,786

occurs for the USDDKK, with a value of USD 163,900,952.

The table reflects the average base currency size of a trade in each currency pair by constructing (total trade volume)/(number of trades) for each day, and then averaging across all days over the 2012–2019 period for the Funds category on CLS.

3.2 *Daily positioning*

Our positioning proxy is the cumulative sum of the daily flows. To be clear, we start with the trade volume at the first day in the sample and then for each additional day compute the cumulative daily flows through that day. One issue is that we do not have insight into the positioning of the CLS participants prior to the start of our sample. However, we can look at positioning in exchange-traded options and futures as an incomplete measure of overall market positioning at the start of our sample.

The data indicate that funds are short EUR/long USD over the entire sample period, trending down over time. Corporates are also short EUR/long USD over the sample, but the short reaches a trough entering 2017 and then is reduced over the remainder of the sample. Nonbank financials switch from an early 2013 short EUR position to long EUR from mid-2013 through early 2017, after which they are short EUR/long USD. Examining the positioning proxy for other currencies versus the dollar reveals a general conclusion that positioning of funds is different from that of other entities.[8]

Since we do not have a starting observation on CLS positioning, we examine the exchange-traded positioning data from the Commitment of Traders (COT) report published by the CFTC to infer the sign of positioning at the start of the sample. The COT data we examine are for futures and options positions of noncommercial entities, which are largely speculators. Commercial entities are largely hedgers. The COT data show that in the late-2012 when our data begin, the market is short EUR, but the position shifts to long EUR at times during the year. Positioning in GBPUSD is essentially flat at the start of the sample. For the JPY, there is a small long position at the start of the sample. Since exchange-traded options and futures are a small part of the FX market, this snapshot of positioning from the COT is considered suggestive, but not authoritative.

4 CLS Data-Based Trade Strategy: Intraday Portfolio Construction

In this section we aim to develop a trading strategy which exploits the information in the CLS data. We will explore different approaches that leverage both qualitative and quantitative inputs, with the aim of finding tradable patterns. Finally, we will proceed to build portfolios and develop a trading algorithm.

Our investment strategy is to use trade flows of market participants as a trading signal. Similar trade flows strategies have been used by many of the studies cited in Section 3. We view the trades of investment funds as trading done with a view toward future exchange rates. Menkhoff *et al.* (2016) find that investment funds have the largest predictive power for exchange rates. We will construct a strategy that takes long positions in currencies being bought by investment funds and short positions in currencies being sold by the funds. In addition, we view the trades of corporate entities as uninformed liquidity trading. Particularly relevant is Ranaldo and Somogyi (2021) who also use CLS data and find that corporate trades have smaller effects and opposite signs on exchange rates than funds. We will exploit this view for a risk management overlay on our investment strategy.

4.1 Intraday strategy

4.1.1 Fund signals

As pointed out in the prior section, funds data appear to be the most useful for predicting exchange rates as funds trade financial assets with a view toward profits from fluctuations in exchange rates. On the contrary, corporate trades are more likely driven by liquidity motives rather than FX investing. Therefore, the first trading model is built upon the hourly data regarding fund flows and positioning.

The first aspect to consider is the training period; this refers to an initial stage in which we do not trade but use the data to provide initial measures of the metrics that underlie the trading strategy. In our model, the training period will span from October 01, 2012 to December 31, 2012 for a total of 3 months of hourly data, i.e. 20 observations per day (more on trading hours later). To be more specific, we will look at two types of statistics: flow and positioning. The former refers to a single observation represented by a trade, e.g. a fund trading 1 million in EURUSD, while the latter refers to the cumulative volume, i.e. the positioning that funds hold in every currency. The positioning statistics are non-trivial to measure, as we have to assess the positioning for each hour of the day. In other words, we have to account for the fact that a position might look quite large at 01:00 AM London time while looking modest at a peak hour such as 16:00 PM London time. Thus, we have to carefully train the data and store this complex schema of statistics to be able to direct our trades. Once the trading simulation starts, we will repeat the same process every month, in an expanding window fashion so that we maximize the amount of information and feed the model with the most accurate statistics possible.

The next step is to lay out the trading rules that govern a benchmark model:

(1) Trading hours: 00:00–20:00 London time

The reason behind this choice is that we want to capture the entire FX market, namely Asia, Europe, and the US. The last 4 hours of the day are omitted, as the market is quite illiquid at this time.

(2) G10 currencies versus USD

The focus of the strategy is the most traded currencies, paired with the USD. We have a base portfolio in USD and create a straightforward portfolio that avoids complications with cross-currency trades.

(3) Trade size: $1 million

At this stage, we will trade a fixed amount of USD regardless of the signal strength and the G10 currency that we are trading. In later models, the trade size will be part of a further optimization.

(4) Portfolio value: $100 million

This figure is less important in the sense that the model is scalable; we just need to ensure that the starting value is an appropriate size to accommodate all the trading signals coming from the model.

(5) Trade in the same direction as fund flows intraday until one of the following happens:

(a) Fund flow reverses by more than 1 standard deviation: this means that we observe a flow with opposite sign to what we hold, e.g. we are long EUR but the funds flow is selling EUR, and this reverse flow is significant enough for us to close the position, i.e. is 1 standard deviation greater than the average flow.

(b) Fund positioning is 2 standard deviations larger than average; here we are looking at the cumulative trades, i.e. positioning. If we see that the cumulative trades are especially large, then we believe that positioning is getting crowded and the possibility for a large adverse exchange rate move is higher, so we close the position.

(c) We reach the end of the day: we only hold the position intraday and do not hold anything overnight.

The performance of this simulation is summarized in Figure 2 and Table 2.

Table 2 Intraday strategy (1) performance metrics.

Annualized return	2.05%
Annualized standard dev	2.73%
Return/risk ratio	0.75
Max drawdown	−6.17%

The strategy incurs a long period of poor performance in 2015–2016 but yields positive returns over the full sample with an information ratio of 0.75. We will treat this as a useful benchmark for the next models.

4.1.2 Funds and corporate signals

In this section, we add the corporate data. Earlier we asserted that corporate FX trades are "uninformed," meaning that they are not seeking profits from exchange rate changes and do not reflect information regarding future exchange rate changes. Corporations trade currencies to finance the needs of their business. For instance, Volkswagen in Germany may sell US dollars for euros as the consequence of US dollar receivables. If the dollar sale is particularly large, it may have a temporary effect of dollar depreciation versus the euro. However, since this is a

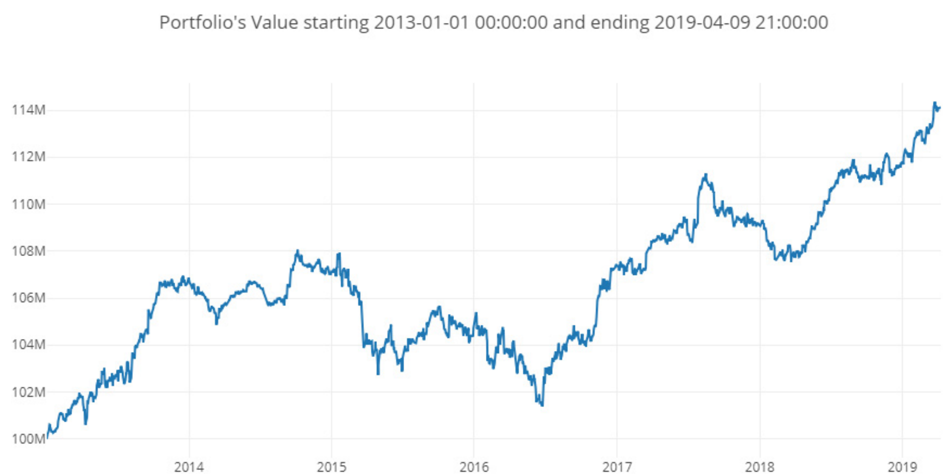


Figure 2 Intraday strategy (1) cumulative portfolio value.

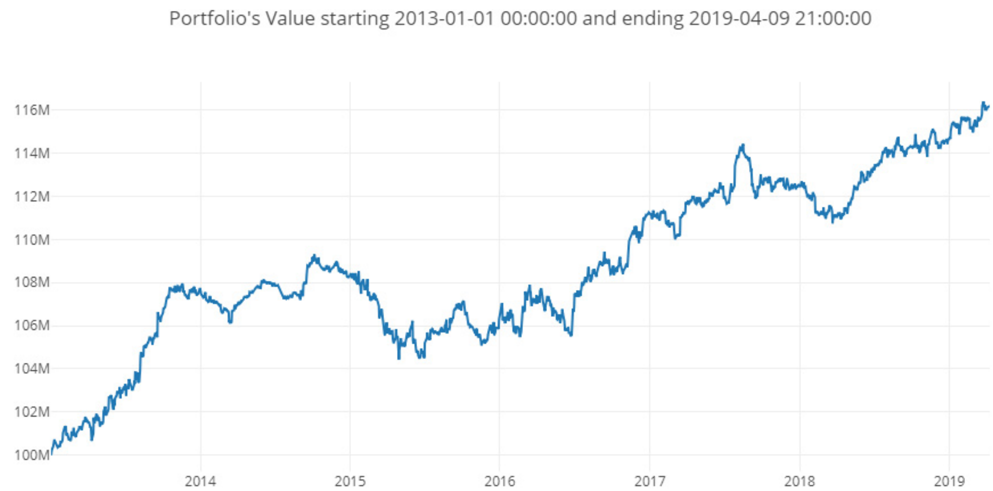


Figure 3 Intraday strategy (2): funds + corporate, cumulative portfolio value.

one-off transaction and is not done with a view toward future exchange rates, once the market has digested that large flow, the exchange rate will tend to revert back to where it was prior to the trade. Although this might lead us to completely disregard the data, there is still important information that we can extract from a corporate trade: price impact. If the corporate flow is large enough, it will move prices and therefore represent a trading opportunity. Because of its liquidity motivation rather than seeking profit from future exchange rate moves, the corporate-trade-related price fluctuation should reverse as the market incorporates the information that the fluctuation was not caused by any news and the flow does not continue to follow the same direction.

Thus, we will add a sixth rule to our trading model:

(6) Bet on reversal if we observe a large corporate flow, i.e. greater than or equal to 2 standard deviations away from the average corporate trade. Specifically, we will go short if the big flow is a buy and vice versa for a sell. Next, we will close the position the following hour, based on the intuition that the market will quickly incorporate the information and update prices.

Table 3 Intraday strategy (2) performance metrics.

	Portfolio
Annualized return	2.34%
Annualized standard dev	2.64%
Return/risk ratio	0.89
Max drawdown	−4.46%

The performance of this trading strategy is summarized in Figure 3 and Table 3. The performance of the strategy improved by including the corporate data and related trading rule into the model. The information ratio is now 0.89.

4.1.3 Transaction costs

Although both strategies show positive performance over the sample, we have yet to consider an important issue: transaction costs. We must account for the costs of trading to infer if the hourly trading strategy is profitable after costs. Transaction costs are directly proportional to the number and size of trades placed every day. We use trading cost data from Melvin *et al.* (2020). These are average "sweep to fill" costs from the major electronic brokerages for FX. Table 4 shows

Table 4 Transaction costs of $1 million trade.

	EURUSD	GBPUSD	AUDUSD	NZDUSD	USDJPY	USDCAD	USDSEK	USDNOK	USDCHF
Cost	0.47	0.9	1.09	1.62	0.53	0.96	2.14	2.81	1.07

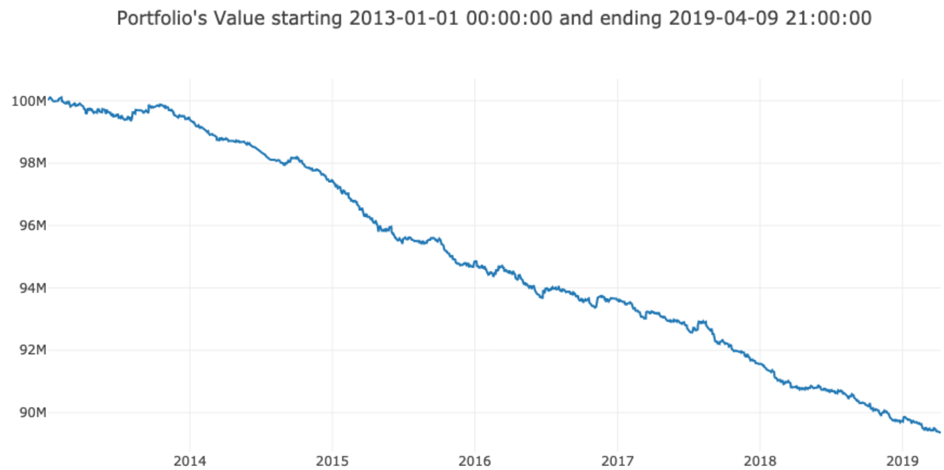


Figure 4 Intraday strategy (3) funds + corporate with transaction cost.

the top-of-order-book half-spreads, which will be the actual cost for a $1 million trade.

We can interpret these figures in the following way: each trade will cost half the spread, which is the magnitude shown in the table. So if we have a trade size of $1 million, the costs in basis points would be 0.47 bps for EUR, 0.53 bps for JPY, etc.; so for a $1 million EUR trade, we would pay 0.000047 in costs or $47, which should be deducted from the profit (or loss) on that trade.

The table shows half-spreads in basis points from the major electronic crossing networks for currencies.

The first observation here is that less liquid currencies such as NOK or SEK are substantially more expensive than EUR or GBP. Thus the profit earned from a trade can be easily overwhelmed by its transaction costs, especially because we are trading on such small-time intervals, i.e. a few hours, where prices do not present large fluctuations.

The intraday strategy trades often. Over the entire period of the simulation, the model trades 128,975 times from the funds signal and 3,627 times from the corporate signal. Such turnover turns out to be too high once we include transaction costs in the strategy, as Figure 4 and Table 5 illustrate. We can clearly see how transaction costs dominate the intraday profit. The intraday strategy trades too much and the transaction cost hurdle is too high.

4.2 Daily strategy

This section implements a different approach in which we study daily data instead of intraday data. It is important to think carefully as to why and

Table 5 Intraday strategy (3) performance metrics with transaction costs.

Annualized return	−1.72%
Annualized standard dev	0.65%
Return/risk ratio	−2.65

Figure 5 Daily strategy (1) funds flows only.

how we are moving to a daily frequency from an hourly frequency. We already explored one reason of the "why," namely transaction costs; an additional reason reflects the approach in general. Specifically, if we are trading on hourly data, we are probably too slow for a high-frequency trading model and too fast to incorporate medium-term expectations of the market. It is key to mention that moving to a daily strategy is not only a change of frequency, but also a change of insight and expectations. Now, we will hold positions overnight and we will use an aggregate measure of daily volumes, exploiting the medium-/long-term expectations that investment funds have on the FX market.

Digging deeper into the "how," we will group fund flows summing all the trades placed every day and will trade on the prices at 08:00 AM London time, using the prior day's data. The trading rules will not change, but it's key to remember that now these rules reflect a different approach and view of the market. We still trade with fund flows, until a large reversal flow is observed, and trade against corporate flows. We also still use cumulative positioning as a risk management tool measuring crowded positions that are exited once identified.

When first simulating the daily strategy, we noticed that there was a very large positive return realized on January 15, 2015. This was the day that the Swiss National Bank ended the CHF peg to the euro and there was a dramatic appreciation of the CHF against the euro as well as other currencies. The USDCHF exchange rate jumped from 1.0227 to 0.8339. Our model was correctly positioned long CHF on this day which resulted in a huge positive return to the strategy. We are not asserting that the model can correctly anticipate large market surprises, but that we were lucky in being correctly positioned for the SNB action. We view the effect of the SNB action on returns as an outlier event that distorts the true performance of the model. For this reason, we will start the rest of the simulations on January 19, 2015 in order to avoid the outlier event and its effect on portfolio return.

In order to assess the value of the corporate flows, we simulate the trading strategy first with only the informed fund flows and then repeat the exercise incorporating the uninformed corporate flows. All simulations incorporate transaction costs. Figure 5 and Table 6 show the performance of the strategy incorporating transaction costs. In this case, the strategy was able to withstand transaction costs, which were the main detractor in the intraday strategy of the previous section. To

Table 6 Daily strategy (1) performance metrics.

	Portfolio
Annualized return	0.67%
Annualized standard dev	0.52%
Return/risk ratio	1.28

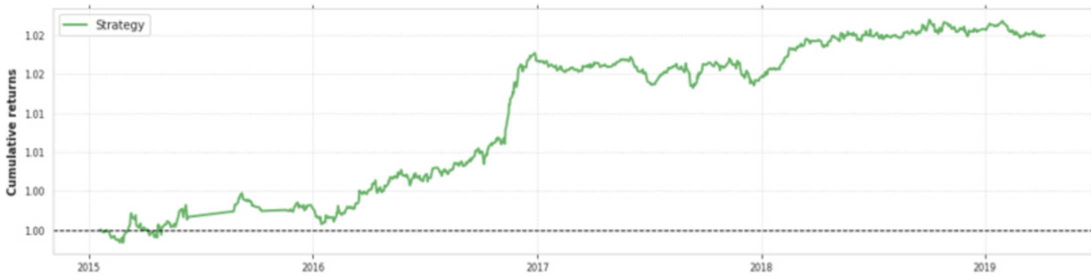


Figure 6 Daily strategy (2) fund and corporate flows.

Table 7 Daily strategy (2) performance metrics.

	Portfolio
Annualized return	0.63%
Annualized standard dev	0.49%
Return/risk ratio	1.29

see the value added by corporate flows, the simulation is rerun with results reported in Figure 6 and Table 7. The results are quite similar and it does not appear that the incorporation of the corporate flows added much, if anything to the daily strategy using this approach to portfolio construction.

An obvious concern with the returns reported in Figures 5 and 6 is the fact that performance was outstanding in 2016 and fairly flat otherwise. This inconsistency is a problem for the strategy that we have utilized so far. We will next turn to optimized portfolios for a daily trading strategy and explore the implications for the value of trading the flows information.

5 CLS Data-Based Trade Strategy 2: Portfolio Construction with Optimization

In this section, we now use optimization techniques to construct the portfolio and simulate backtests. We begin with a standard currency momentum model and then explore the gain from adding the flows data beyond a generic currency signal like momentum.

5.1 Momentum strategy

We start with the momentum portfolio, where the approach is a straightforward mean/variance optimization. The objective function is:

$$\max_h \{h^T\alpha - \lambda h^T Vh - \theta(h - h_{prev})^T \mathrm{diag}(TC)(h - h_{prev})\} \quad (1)$$

where h represents holdings or positions of the different currencies in the portfolio; α is expected return, as proxied by the recent price trend, measured as the lagged 22 day return; λ is a risk aversion parameter; V is a covariance matrix computed over the past month; θ is the sensitivity to transaction costs (sometimes call the "amortization factor"); *TC* is a vector of transaction costs for each currency; and h_{prev} is the lagged holdings so that $(h - h_{prev})$ is a vector of trade sizes across currencies. As in most institutional currency investment portfolios, we include a risk target for the optimization. While the choice is scalable, we use 10% for our application, or $h^T Vh = 10\%$. The actual realized level of risk varies from the target level as the values of V and h change through time.

As learned in the prior section, incorporating a recognition of trade costs and how they vary across currencies is important in order to preserve any alpha resulting from the strategy. A portfolio construction strategy using this objective function results in the simulation of an implementable strategy by investors.

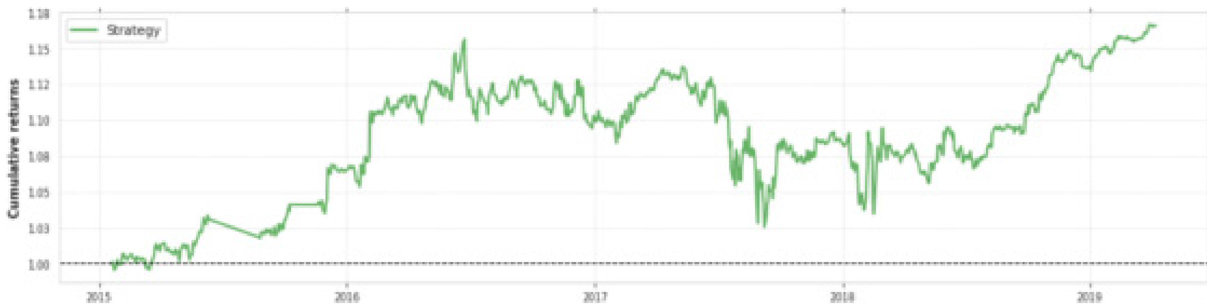


Figure 7 Momentum signal cumulative returns.

Table 8 Momentum signal portfolio performance metrics.

Annualized return	4.00%
Annualized standard dev	7.14%
Return/Risk ratio	0.56
Max drawdown	11.32%
Max drawdown duration	660 days

Results for the momentum strategy are given in Figure 7 and Table 8. Over this period, a simple momentum strategy delivered positive risk-adjusted performance, although with a substantial drawdown period visible from mid-2016 to early 2018.

The sample period was challenging for momentum. The strategy performed well early in the sample and then again late in the sample.

Now we want to add fund flows and then add the corporate flows to examine the contributions of each to an investment strategy. We take the generic momentum strategy as the benchmark strategy and combine that strategy with the flows data in a Black–Litterman framework, where the flows data inform the "views"' of the portfolio manager (PM). Specifically, the model is represented by a specification as follows:

$$E(r) = [(\tau V)^{-1} + P'^{\Omega^{-1}} P]^{-1} \times [(\tau V)^{-1}\Pi + P'^{\Omega^{-1}} Q] \qquad (2)$$

where $E(r)$ is a 9×1 vector of posterior expected returns from combining the momentum and funds signals, τ is a parameter reflecting the confidence in expected momentum returns, V is a 9×9 covariance matrix of returns across currencies, P is a 2×9 matrix of portfolio weights from the flows signals, Ω is a 2×2 matrix of uncertainty (or confidence) regarding the PM views on the two flows signals, Π is a 9×1 vector of returns implied by the momentum strategy, and Q is a 2×1 vector of flows-informed PM expected return views derived from the funds and corporate flows.

A value of τ of 0.05 was chosen by He and Litterman (2002) and is often used in research. However, if we consider momentum as a benchmark strategy and the flows signals as "active" strategies, the currency positions of the portfolio can be segmented into benchmark and active weights and the τ parameter can be used to control active risk. Given a particular target risk, there is an implied value of τ.

With the BL framework in place, we first constrain the view on corporate flows to zero and have funds flows only informing the models views. Results for this funds-flows-enhanced strategy are given in Figure 8 and Table 9. This strategy ran at a higher risk level than simple momentum and risk-adjusted performance increases relative to the simple momentum strategy. It is notable that the maximum drawdown duration was roughly

Figure 8 Fund flows cumulative returns.

Table 9 Fund flows signal portfolio performance metrics.

Annualized return	9.60%
Annualized standard dev	12.20%
Return/Risk ratio	0.79
Max drawdown	13.39%
Max drawdown duration	346 days

cut into half relative to the momentum model. It is also notable that the performance of this strategy was outstanding early in the sample period and then levels off for years.

Lastly, we add the corporate flows signal into the mix and backtest this combined strategy. Results are given in Figure 9 and Table 10. Risk-adjusted performance is enhanced with the addition of the corporate flows and the drawdown is reduced substantially in both magnitude and duration. In addition, the positive performance of the strategy with corporate flows included was more evenly realized through time. There is still a run of outstanding performance in the first year and a half of the backtest and then another excellent run of performance starting in early 2017 through the rest of the sample, with a brief period of drawdown in mid-2018.

The evidence suggests that there is value in enhancing a generic currency-trading strategy with the flows data. Trading in the direction of funds flows added value, though was inconsistent over time in our backtest. Trading against the large flows of corporates added further value and added more consistent performance over time. The corporate flows signal also reduced the duration of the maximum drawdown by almost half. So from both a risk-adjusted returns perspective and a tail-risk management perspective, there is value in using the corporate flows as an integral part of the strategy.[9,10]

Figure 9 Fund and corporate flows cumulative returns.

Table 10 Fund and corporate flows signal portfolio performance metrics.

Annualized return	11.74%
Annualized standard dev	11.53%
Return/Risk ratio	1.002
Max drawdown	12.07%
Max drawdown duration	169 days

6 Conclusions

The CLS settlement system sits at the center of the global currency universe and data on FX trade settlement allow the most comprehensive view of the opaque market of OTC currency trades. We first review the different data sets on currency flows that have been used in prior research and then turn to an analysis of the CLS data.

After a review of the data, we turn to constructing investment models. CLS data are disaggregated into different categories of market participants. We use the flows of investment funds and corporates for our study. Importantly, we interpret these two types of signals differently: the former reflects speculative strategies, while the latter trade for liquidity needs. The implication is that we should trade with the direction indicated by the funds flows and trade against large corporate flows, which should be followed by price reversals.

First, we developed a simple prescriptive trade strategy which trades fixed amounts of currencies in line with the flows signals. For instance, buy \$1 million of a currency when funds flows are positive for that currency and sell \$1 million when corporate flows are positive. Initially we simulate an intraday strategy which traded hourly. Although the model generated attractive pre-cost returns, it ultimately failed after accounting for transaction costs. The turnover associated with the intraday model was too high and too costly, so we then turned to a daily strategy. With the daily strategy, we were able to reduce the number of trades by a factor of 10 and the backtest simulation of the daily model showed an attractive attainable alpha. The major problem for this approach to portfolio construction was the inconsistent performance of the portfolio through time. While performance was excellent at times, there were long periods of underperformance.

We then turned to optimization techniques to allow currency positions and trade size to vary with signal strength. In order to assess the funds signals relative to a generic currency model, we first simulate a simple momentum model. Results showed excellent performance early and late in the sample with a long run of underperformance in the middle years of the sample. We use a Black–Litterman approach to combine the momentum signal with the flows signals. In this construction, the momentum model was the benchmark model and the flows informed the portfolio manager's "views". First we turned off the corporate signal and included only funds flows. The model performance improved relative to the generic momentum model, in terms of both risk-adjusted return and drawdown magnitude and duration. We then added the corporate flows into the model and performance improved further, again for both risk-adjusted return and more dramatically for drawdown magnitude and duration. The addition of the uninformed trades of corporates was quite useful in greatly lowering the tail risk of the model.

Overall, it appears that there is value to the investor of using CLS flows data to construct active currency portfolios. Our strategies are all implementable and incorporate realistic transaction costs.

Appendix

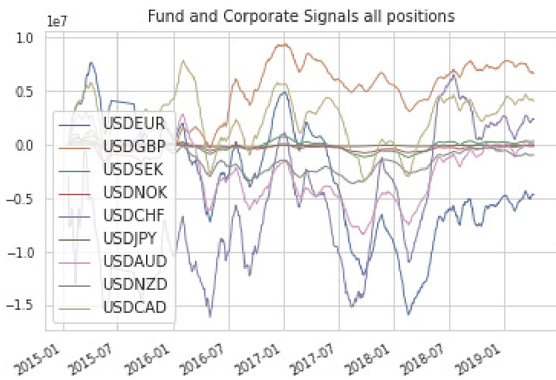


Figure A.1 Currency positions from portfolio optimization including both fund and corporate flows.

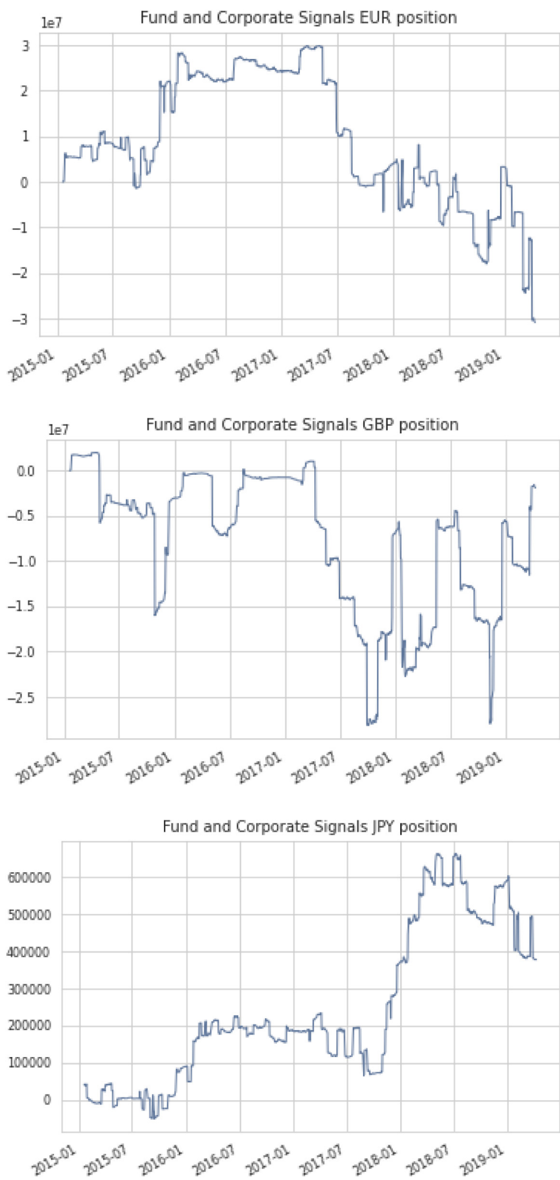
Fund and corporate flows cumulative returns

Figure A.2 Performance of portfolio with three major currencies only (EUR, GBP, JPY).

Fund and corporate flows signal portfolio performance metrics

Annualized return	9.04%
Annualized standard dev	13.58%
Return/Risk ratio	0.665
Max drawdown	17.22%
Max drawdown duration	212 days

Currency positions from portfolio optimization including both fund and corporate flows



Endnotes

1 See Bank for International Settlements (2022) for the last survey report.

2 See Anzuini and Fornari (2012) for a recent paper using the CFTC data to proxy for currency positioning.

3 See Menkhoff *et al.* (2016) or Burnside *et al.* (2020) for an example of studies that use trade data from a single bank and focus on the end-user clients of the bank. Perhaps the earliest study using trade data from a single bank (Citibank), is Evans and Lyons (2005).

4 Froot and Ramadorai (2005) use the State Street data to estimate the impact of investor flows on currency returns. They find that flows can have short-run effects on returns but the effects do not persist through time and tend to be reversed.

5 An early study is Evans and Lyons (2002) while Manciini *et al.* (2013), Ito and Yamada (2017), and Chaboud *et al.* (2022) are recent examples.

6 The list includes Moore *et al.* (2016), Gargano *et al.* (2021), Ranaldo and Somogyi (2021), Hasbrouck and Levich (2021), and Cespa *et al.* (2022),

7 Ranaldo and Somogyi (2021) study the price impact of trades by different type of participant using the CLS data. They find that corporate flows have a smaller price impact than trades by funds or nonbank financials. Their findings for nonbank financials suggest that such flows may also be informative for currency investors to follow.

8 While examining the CLS positioning data, it is interesting to examine the oft-expressed belief that positions are squared as year-end approaches. It is true that as year-end approaches, liquidity typically falls as holidays reduce trading activity and people take time off from work. This is often considered a time when investors cut their positions in order to reduce their exposure to risk. One will frequently see articles in the financial press asserting that position-squaring is in process as year-end approaches. Examples of recent headlines are “US Dollar Rises On Position Squaring in Year-End Dealings” (Delgado, 2017) or “Paring of USD Longs: Position Squaring Ahead of Year End or Worries About the Fed?” (Laidi, 2018). A belief in year-end position squaring applies to other asset classes in addition to currencies, as suggested in “Raw Sugar Rallies in Year-End Squaring Amid Dry India Weather” (Cohen and Brough, 2015); “Pre-holiday Short-Covering and Position-Squaring Underpins Crude Oil” (Hyerczyk, 2015); or “TREASURIES - Year-End Position Squaring Boosts Bonds” (Reese, 2010). The relatively comprehensive CLS positioning data are useful to examine in order to determine if the market folklore is accurate. A review of the positioning series for each currency shows that there is no evidence to support the belief that positions are squared as year-end approaches. There is no reduction of the positions as year-end approaches. This is the general pattern seen across time and trader-type. Using the most comprehensive data on FX positioning available, one cannot find supportive evidence of year-end position squaring.

[9] Appendix 1 shows the positions of the different currencies over time. Appendix 2 shows results if the portfolio is constrained to only trade the 3 major currency pairs of the EUR, GBP, and JPY against the USD. While performance is positive, it is more volatile and offers a lower return and longer and deeper drawdown than the portfolio with all currencies included.

[10] As in all backtested strategies, one must exercise caution when using a particular model for future trading in a dynamic world where conditions can change quickly. In addition, optimized strategies can be recalibrated or modified in many ways that may have a significant effect on risk-adjusted performance.

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