Connecting Equity and Foreign Exchange Markets Through the WM Fix: A Trading Strategy*

Arnav Sheth[†] and Keisuke Teeple[‡]

*The authors would like to acknowledge conversations with David DeRosa and Adam Duncan, data from WM/Reuters, and support from Saint Mary's College of California. We would also like to thank the anonymous referee for their comments. Any errors are, of course, our own.

†Digital Learning Fellow, Massachusetts Institute of Technology, and Associate Professor, Saint Mary's College of California. Corresponding author (shetha@mit.edu).

‡Graduate Student, University of California at Davis.

List of Figures

List of Tables

Abstract

We examine the relationship between equity and foreign exchange markets at, and around, the WM/Reuters benchmark exchange rate known as the the 'Fix'. Execution at the Fix is a service offered by brokers provided they obtain the trade order before 4pm GMT. We have three main goals with this paper: (i) to show a connection between equities and foreign exchange markets via this window; (ii) to leverage this connection using an algorithmic trading strategy; and (iii) to rank various statistical techniques used to make predictions for trading based on their investment results. We are successful in all three endeavors with the best technique producing an out-of-sample annual cumulative return of 4.02% and an annualized Sharpe ratio of 3.43. This strategy is for illustration only.

Key Messages

- We connect equity and FX markets via an algorithmic trading strategy.
- The trading strategy exploits a behavioral anomaly in FX markets.
- We evaluate the efficacy of various statistical machine learning techniques in executing the trading strategy.

Keywords foreign exchange rates, market microstructure, WM/Reuters Fix

This draft: November 17, 2019
Word count: 3123

1 Introduction and Motivation

The "London 4pm Fix" or the "WM/R Fix" or simply the "Fix" is an important currency benchmark in financial markets. It is published at 4pm GMT (11am Eastern Time in the US) by the WM Company and Reuters based on forex trading around the 4pm mark. Execution at the Fix is a service offered by brokers (normally banks), who deliver it provided they obtain the trade order until a certain time prior to 4pm. As it provides standardization of currency prices, most international fund managers value the foreign exchange exposure of their international equity portfolios using the Fix. Furthermore, they also use the Fix to hedge their international equity portfolios using derivative contracts, which are also valued at the Fix. And finally, tracking error for portfolio manager performance is also measured using the Fix. Thus, it is a critical component of international equity trading, and a key element in forex markets.

Prior literature on this includes Melvin and Prins [2015], Melvin and Prins [2013], Evans [2014], Michelberger and Witte [2015], El Mouaaouy [2015] and and Ito and Yamada [2015]. There are also a few industry white papers (Pragma Trading [2015] and Cochrane [2015]). The work closest to our study is Melvin and Prins [2015], who use past equity returns to identify directions of hedging trades by portfolio managers, and use those to predict the direction of the Fix at the ends of months. We go one step further and predict movements of the Fix on a daily basis, using opening values of a variety of stock index benchmarks, and we create a trading strategy based on this.

We begin with the assumption that equity portfolio managers are using the Fix to either hedge their trades, or buy and sell more equity, and based on that we test for the predictability of the WM Fix using equity indexes, and use a logistic regression to calculate probabilities of accuracy. We trade based on our model and find that we make a modest positive profit over the period of one year.

Given our success in this endeavor, we further hypothesize that hedging activity is positively correlated with momentum. In other words, if stocks are going up, and are continuing to go up, managers will tend to buy more of them, and vice versa. We hypothesize that this should also happen through the Fix, and so we study the relationship between the Fama French momentum factor and foreign exchange rates, especially around the Fix. We do the same with expected volatility as measured by the VIX index, under the assumption that increased volatility leads to increased buying or selling around the Fix. And finally, based on Cenedese et al. [2016], we also include a dividend yield proxy, and the term spread.

Please note that this strategy is for illustrative purposes only.

2 Literature Review

As mentioned in the earlier section, prior academic literature includes Melvin and Prins [2015], Evans [2014], Michelberger and Witte [2015], El Mouaaouy [2015], and Ito and Yamada [2015].

Melvin and Prins [2015] use past equity returns to test the hypothesis that hedging around the Fix affects exchange rates. Their main hypothesis is that hedging trades generated by outperformance of a country's equity market over the course of a month, relative to other months, will lead to selling of the country's currency up to the end-of-month (EOM) Fix. They test the hypothesis that the relationship of equity and currency markets is negative and find statistical significance in this regard. They also present a model (a variation of Hau and Rey [2006]) that shows that rebalancing and hedging and interchangeable from an economic point-of-view. Evans [2014] looks at the behavior of exchange rates around the Fix, also citing hedging behavior by managers, and finds a negative autocorrelation with exchange rates between pre- and post-Fix periods, particularly at the end of the month.

Both Melvin and Prins [2015] and Evans [2014] discuss the incentive for portfolio managers to fill their orders at the Fix, in order to minimize any error in valuation of their portfolios. And furthermore, that these orders are filled mostly at the end of the month.

Similar to Melvin and Prins [2015] and Evans [2014], Michelberger and Witte [2015] looks at local extrema in price and volatility around the London 4pm Fix. They conclude that spikes around the Fix can be distinguished from those at the rest of the day, and thus results in an increased probability of spot rate extreme in the Fix window. They conclude that the consequence of this compression of large order flow into the narrow time window of the Fix is a higher implicit cost of trading for the investor.

Unlike the previous studies, El Mouaaouy [2015] and Ito and Yamada [2015] focus more on the collusive and regulatory aspects of the Fix as a consequence of the increased scrutiny by international financial regulatory bodies beginning in the late-summer of 2013. El Mouaaouy [2015] constructs two "manipulation measures" to test for the probability and intensity of potential misconduct in the period surrounding the Fix. Ito and Yamada [2015] look for evidence of manipulation by looking at both, the Tokyo Fix[1] as well as the London Fix. Like the other studies cited here, they too look at spikes in the prices and compare those around the Tokyo and London Fix; they look at market depth (liquidity) and find there is plenty of it; and they conclude that there is no direct evidence of market manipulation.

Most recently, Cenedese et al. [2016] look at the relationship of equity markets and foreign exchange rates. Though not related to the Fix, per se, they do provide some insights which we take into account.

3 Data

Apart from the WM/Reuters Fix data which was kindly provided to us by WM/Reuters, we use only publicly available data sources for our study: histdata.com for foreign exchange data, finance.yahoo.com for equities and VIX data, and Ken French's Data Library for data on the momentum factor.

We look at ten currency pairs, all in terms of US dollars, as our primary market for our strategy is the United States. The eight currencies are:

1. EURUSD (Euro)
2. GBPUSD (British Pound)
3. USDCHF (Swiss Franc)
4. USDJPY (Japanese Yen)
5. USDCAD (Canadian Dollar)
6. AUDUSD (Australian Dollar)
7. NZDUSD (New Zealand Dollar)
8. USDSEK (Swedish Kroner)
9. USDNOK (Norwegian Kroner)
10. MXNUSD (Mexican Peso)

For each currency pair, we train our model across four years of data: 2012-15 (inclusive), and then test for the strategy out-of-sample in 2016.

[1]Note that the methodology in Tokyo is slightly different since prices are set by individual banks rather than as a function of market prices. Further, the price is released at the start of the trading day as opposed to London where it is released at the end of the trading day – 4pm GMT.

We test for predictability for each currency pair above with thirteen separate equity benchmark indicators and the term spread. In other words, our independent variables for each currency pair are:

1. S&P 500 (US)
2. DAX (Germany)
3. SSMI (Switzerland)
4. Nikkei 225 (Japan)
5. S&P/TSX (Canada)
6. ASX (Australia)
7. NZX 50 (New Zealand)
8. OMX (Sweden)
9. FTSE (UK)
10. IPC (Mexico)
11. VIX
12. Dividend Yield Proxy (VYM)
13. Term Spread
14. Momentum Factor

We add the dividend yield proxy and the term spread based on Cenedese et al. [2016] who find explanatory power in these two variables for exchange rates.

All times will henceforth be in Eastern Time in the US. We ignore changes in Daylight Savings Time (DST). The United Kingdom also has DST, and the date when DST goes into effect across both countries differs by a week; the date when DST goes out of effect differs by two weeks. Given that we are looking across entire years, including for these effects will not affect our main results.

4 Results

4.1 Regression Analysis

As part of our analysis, we wish to examine predictability of both foreign exchange returns and volatility between 10 am and 11 am using equities. As stated earlier, equity portfolio managers use the Fix to trade foreign stocks, measure tracking error (so are more prone to trade at the Fix), and value equity (and other) derivative contracts at the Fix. To that end, we run univariate regressions (to avoid issues of multicollinearity) to test for predictability of the 11 am exchange rates using daily data[2].

Since we are trying to create predictive relationships, i.e., using equity to predict the 11 am foreign exchange rate, we use opening values for equity data (which is daily), and for our foreign exchange data (which is minute-by-minute) we use closing bids. We measure returns in the following manner:

Equity Returns are calculated as a rolling 21-day percent difference. For example, returns for the 28th of a given month would be:

$$\frac{\text{28th Open} - \text{7th Open}}{\text{7th Open}}$$

[2] At first, we ran regressions separately on EOM days, given the nature of the difference we have seen between EOM and non-EOM days in our visual analysis presented earlier. However, we found little or no significance in the relationships on EOM days. All of the significance, it seems, comes from the non-EOM days. This runs somewhat counter to our initial hypothesis that managers trade mostly at the end of the month, but given this surprising result, we continue our exploratory analysis and include all days (EOM and non-EOM) in our regression analysis.

Equity Volatility is calculated over daily returns (Open to Open), and the standard deviation is taken over 21 days of returns.

Foreign Exchange Returns are calculated simply as the percent difference between the 10 am price and the 11 am price. We assume we buy at 10 am and sell at 11 am.

$$\frac{\text{11 am Close} - \text{10 am Close}}{\text{10 am Close}}$$

Foreign Exchange Volatility is calculated over rolling 5-minute returns between 10 am and 11:30 am. Thus, we get a series of 5-minute returns from 10 am to 11:30 am, and calculate the standard deviation of that series.

For the equity returns, we focused on a rolling window of 21 trading days, which is approximately equal to a calendar month. Of course, each equity portfolio manager likely operates very differently, but we settled on this timeframe based on Melvin and Prins [2015] finding that end-of-month periods have greater significance and also that tracking error and performance are usually measured monthly[3].

For the one-hour window before the Fix, based on interviews we were told that market liquidity is maximal in that period. On exploring a few other windows we did not see any significant difference in results, though our chosen one did give us slightly superior returns.

We focused on the US markets only, and as we were looking at this from the perspective of US equity portfolio managers, we work under the assumption that they look at data once markets open there. This also helps us with computational simplicity; if we incorporate all other time zones into the code, it can get very complex, particularly since we are attempting to automate the strategy. We are considering various other perspectives (e.g., from the perspective of Japanese equity portfolio managers) for our future work.

4.2 Ordinary Least Squares

In order to avoid the issue of multicollinearity, and to get a sense of the relationships in the data, we start by running a series of univariate regressions with the equity-based values on the right-hand-side, and the foreign exchange values on the left-hand-side. We regress foreign exchange **returns** against equity **returns** and **volatility**. In other words, we run the following regressions:

$$\text{FX returns} \sim \text{Equity returns}$$
$$\text{FX returns} \sim \text{Equity volatility}$$

Table 1 has the results of the first of these sets of univariate regressions – those of FX returns on equity returns. Using a rough cutoff p-value of 0.1, we find that 56% of the regressions prove to be significant, and 49% when we adjust these for heterescedasticity, and autocorrelation (HAC) i.e., the Newey-West p-values. We also find that the relationships with equity indexes are mainly positive. In other words, increases in equity indexes indicate a weakening of the dollar from 10 to 11 am. Furthermore, momentum and dividend yield coefficients are negative, significant to the dollar which indicates that increases in momentum and dividend yield, are followed by a strengthening of the dollar. The VIX is also positive, significant to the dollar, across 60% of the currencies, showing that increases in the VIX lead to a weakening of the dollar.

Table 2 has the results of the second of these sets of univariate regressions – those of FX returns on equity volatility. Once again using a rough cutoff of p-value of 0.1, we find that 48% of the regressions prove to be significant, and 42% when we adjust these for heterescedasticity, and autocorrelation (HAC) i.e., the

[3]Based on referee comments, we do plan to vary this window for future research.

Legend	$p<0.1$	$p<0.05$	$p<0.01$

Coefficients$*10^2$*

	S&P	**DAX**	**SSMI**	**Nikkei**	**TSX**	**ASX**	**NZX**	**OMX**	**FTSE**	**IPC**	**VIX**	**Div**	**Term**	**Mom**
EURUSD	6.26	7.85	7.50	7.87	4.31	4.74	6.17	7.39	9.34	5.24	9.21	-13.40	6.75	-7.45
GBPUSD	9.44	12.36	12.06	12.93	5.02	6.00	7.95	11.55	14.90	6.43	15.04	-17.20	8.65	-5.79
CHFUSD	1.63	7.48	6.73	6.06	0.90	1.89	4.06	5.70	6.98	2.43	5.10	-10.08	8.49	-13.67
JPYUSD	1.70	3.07	5.55	3.55	4.19	2.08	-2.99	1.43	5.66	2.19	6.76	-8.86	6.81	-7.90
CADUSD	6.07	5.63	3.84	5.83	2.54	2.58	4.84	7.55	7.01	2.92	7.02	-5.28	2.76	-9.56
AUDUSD	3.41	4.26	1.04	2.79	0.43	0.29	0.51	6.37	2.76	1.78	4.41	-5.56	5.00	-4.81
NZDUSD	4.89	6.06	4.44	4.39	2.54	4.84	2.52	6.98	5.59	2.97	3.98	-8.20	5.15	-5.54
SEKUSD	9.44	9.06	8.74	9.56	7.03	5.62	5.34	12.29	11.06	9.53	10.10	-14.79	5.40	-6.91
NOKUSD	10.04	9.66	6.46	10.15	3.11	5.06	4.41	11.15	9.03	7.18	8.76	-8.94	1.55	-11.35
MXNUSD	3.51	-1.74	-3.01	-2.26	-0.12	-2.96	-1.39	-1.09	-0.72	-4.89	2.61	1.99	2.59	-10.70

Table 1: Linear univariate regressions of FX ***returns*** *(dependent variables, rows) on equity* ***returns*** *(independent variables, columns). We find 56% of the regressions have p < 0.1, and 49% with HAC-adjusted (Newey-West) p-values < 0.1.*

Newey-West p-values. In short, increasing equity index volatilities, where significant, have a weakening effect on the dollar. This substantiates what we saw earlier with the VIX – historical volatilities, and implied volatility have a similar effect on foreign exchange rates. Also, momentum and dividend yield volatility, both continue to have a strengthening effect on the dollar. Does this indicate that greater volatility leads to greater uncertainty leading to greater trading through the Fix?

Legend	$p<0.1$	$p<0.05$	$p<0.01$

Coefficients$*10^2$*

	S&P	**DAX**	**SSMI**	**Nikkei**	**TSX**	**ASX**	**NZX**	**OMX**	**FTSE**	**IPC**	**VIX**	**Div**	**Term**	**Mom**
EURUSD	-8.73	-7.30	-8.82	-9.68	-10.10	-9.63	1.46	-8.73	-11.72	-9.40	-7.94	-8.36	-7.53	-4.74
GBPUSD	-13.95	-10.88	-13.78	-12.69	-12.90	-12.92	-0.37	-13.87	-15.70	-11.16	-11.43	-11.05	-6.37	-7.93
CHFUSD	-10.33	-9.43	-9.27	-9.85	-12.05	-7.46	-0.57	-8.77	-12.01	-9.79	-10.01	-12.70	-8.48	-5.53
JPYUSD	-10.41	-6.87	-9.88	-7.75	-5.62	-7.39	2.64	-7.88	-9.59	-7.43	-8.30	-9.86	-7.35	-4.07
CADUSD	-3.90	-3.20	-2.76	-4.71	-0.75	-3.69	2.56	-4.70	-3.98	-1.39	-3.11	-0.47	-0.47	-1.58
AUDUSD	-4.34	-3.89	-4.02	-4.62	-3.46	-3.52	1.47	-4.82	-4.50	-2.51	-1.85	-3.58	-2.74	-0.35
NZDUSD	-6.59	-7.24	-6.08	-7.43	-7.38	-5.14	-1.00	-7.44	-7.31	-7.43	-4.14	-5.26	-5.74	0.23
SEKUSD	-3.72	-3.09	-4.29	-4.56	-4.02	-4.33	0.68	-5.10	-6.46	-6.78	-4.00	-4.51	-8.47	-1.15
NOKUSD	-1.79	-2.50	-1.44	-2.31	-4.57	-5.54	-0.19	-4.82	-4.77	-6.31	-1.83	-1.40	-10.26	2.92
MXNUSD	-1.73	-3.13	1.43	-1.47	-0.71	1.20	5.30	-2.58	0.13	1.16	-1.47	2.77	1.26	-0.92

Table 2: Linear univariate regressions of FX ***returns*** *(dependent variables, rows) on equity* ***volatilities*** *(independent variables, columns). We find 48% of the regressions have p < 0.1, and 42% with HAC-adjusted (Newey-West) p-values < 0.1.*

In sum, if we use p < 0.1, as a standard, the 'winners' are:

- Dividend Yield and Momentum (9 out of 10 currencies).
- OMX and FTSE Rtns (8 out of 10 currencies).
- Term Spread and the IPC/Mexico Stdevs (7 out of 10 currencies).
- FTSE Stdev (6 out of 10 currencies).

We also see that there are strong correlations between our independent variables. We find high correlations between the returns, and the standard deviations, but not with each other. Table 3 shows the correlation matrix across all 28 variables (14 equity return variables, and 14 equity volatility variables).

Given this problem, we turn to principal component analysis for further study.

Table 3: Correlation Matrix across all 28 variables (14 equity return variables, and 14 equity standard deviation variables). The darker the shade, the higher the correlations, the lighter the shade the lower the correlations, with white indicating a small correlation (i.e., ≤ 0.2).

	Returns														Volatilities													
	S	**D**	**S**	**N**	**T**	**A**	**N**	**O**	**F**	**I**	**V**	**D**	**T**	**M**	**S**	**D**	**S**	**N**	**T**	**A**	**N**	**O**	**F**	**I**	**V**	**D**	**T**	**M**
S	1																											
D	.6	1																										
S	.6	.7	1																									
N	.8	.8	.8	1																								
T	.5	.4	.5	.5	1																							
A	.7	.5	.5	.6	.2	1																						
N	.6	.6	.6	.6	.4	.6	1																					
O	.7	.9	.7	.9	.5	.6	.6	1																				
F	.7	.8	.9	.9	.5	.6	.7	.8	1																			
I	.6	.7	.7	.8	.4	.6	.6	.8	.7	1																		
V	.7	.6	.7	.8	.5	.4	.4	.7	.8	.5	1																	
D	.6	.7	.8	.8	.5	.5	.5	.7	.8	.7	.6	1																
T	.1	.1	0	.1	.1	.1	.1	.1	0	.2	.1	0	1															
M	0	0	0	.1	0	0	0	0	0	0	.1	.1	0	1														
S	.2	.3	.2	.1	.1	.2	.2	.2	.3	.1	.3	.2	.2	0	1													
D	.2	.3	.2	.1	0	.2	.3	.2	.2	.1	.3	.1	.3	0	.8	1												
S	.2	.3	.2	.2	0	.2	.3	.2	.3	.2	.3	.3	.2	0	.8	.8	1											
N	.2	.4	.3	.2	.2	.2	.4	.3	.3	.2	.3	.3	.2	0	.9	.9	.9	1										
T	.1	.2	.2	.1	.1	.1	.1	.1	.2	.1	.2	.2	.1	0	.7	.6	.7	.7	1									
A	0	.3	.1	.1	.1	0	.1	.1	.2	.1	.2	.2	.3	.1	.6	.5	.6	.5	.5	1								
N	.1	.2	.1	.1	.1	.1	.2	.1	.1	.1	.1	.2	.1	0	.3	.2	.4	.3	.3	.4	1							
O	.2	.4	.2	.2	.1	.3	.3	.3	.3	.2	.3	.2	.3	0	.8	.9	.8	.8	.6	.5	.1	1						
F	.2	.4	.3	.2	.1	.2	.3	.3	.4	.2	.3	.3	.2	0	.8	.8	.9	.9	.7	.7	.3	.9	1					
I	.1	.3	.3	.1	.1	.2	.2	.2	.3	.3	.2	.3	.2	0	.7	.7	.7	.8	.7	.5	.3	.8	.8	1				
V	.2	.3	.2	.2	.1	.2	.3	.2	.3	.2	.3	.2	.3	0	.8	.8	.8	.9	.7	.6	.3	.8	.9	.8	1			
D	.1	.4	.3	.2	.2	0	.2	.2	.3	.2	.3	.4	.2	0	.6	.6	.8	.7	.4	.4	.3	.5	.7	.6	.7	1		
T	.2	.3	.3	.3	.3	.2	.1	.3	.3	.3	.3	.4	0	0	.4	.3	.3	.4	.5	.4	.2	.4	.5	.5	.5	.3	1	
M	0	0	0	0	.1	.1	.2	0	0	0	.1	0	.4	0	.6	.6	.6	.6	.4	.2	0	.6	.6	.4	.6	.4	.1	1

4.3 Principal Component Analysis

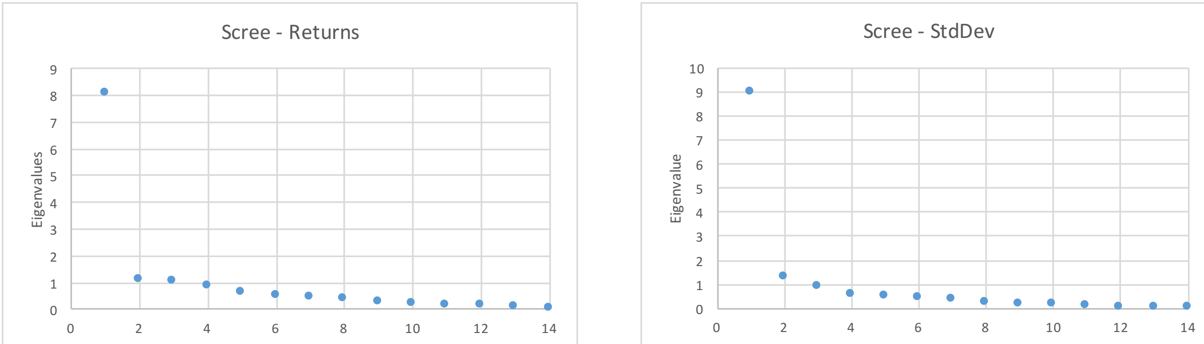
Since our time series are highly correlated with each other, and we wish to make our model a little more parsimonious, we turn to principal components analysis (PCA) to reduce the 28 series down to a few significant factors. As the returns are not correlated with the standard deviations, we run separate analyses on the returns and the volatilities.

4.3.1 Principal Components Analysis: Set #1 (All Relevant Factors)

Figure 1 shows the scree plots of the eigenvalues for each of the two analyses that we run. If we use the controversial 'eigenvalue ≥ 1' rule, we find that four returns factors and three standard deviation factors seem to have some explanatory power. This factor subset also explains approximately 80% of the variance of each of the returns and standard deviations.

We run multivariate regressions of all the factors on each of the ten currency pairs to confirm the PCA output (see Table 4). We do not find support for the factor subset. In fact, we find that the first and second returns factors are significant across most coefficients, as is the first standard deviation factor. Looking at the scree plots, we find sharp drops after the first factors. Given that both, regression analysis and the scree plots support it, we choose this factor subset (two returns factors, and one standard deviation factor) to trade on. In sum, we find that:

- Returns Factors 1 and 2 collectively have 65% coefficients with $p < 0.1$, 75% with HAC-adjusted-$p < 0.1$.
- Returns Factors 3 and 4 collectively have 35% coefficients with $p < 0.1$, 30% with HAC-adjusted-$p < 0.1$.
- Stdev Factor 1 collectively has 40% coefficients with p, and HAC-adjusted-$p < 0.1$.
- Stdev Factors 3 and 4 collectively have 30% with $p < 0.1$, 10% with HAC-adjusted-$p < 0.1$.



(a) Returns Scree Plot

(b) Volatilities Scree Plot

Figure 1: The scree plots for each of the 14 × 2 eigenvalues we retrieve from the principal components analyses. Using the controversial 'eigenvalue ≥ 1' rule, we find that 4 returns factors and 3 standard deviation factors seem to have some explanatory power.

Table 4: The table below contains the summarized regression results of running multivariate regressions of all seven factors across each of the ten currencies. The numbers below indicate how many currencies showed significance for each of the factors.

	# Currencies with	
Factor	**p<0.1**	**HAC p<0.1**
Rtns Fac 1	5	5
Rtns Fac 2	8	10
Rtns Fac 3	5	5
Rtns Fac 4	2	1
Stdev Fac 1	4	4
Stdev Fac 2	2	0
Stdev Fac 3	1	1

4.3.2 Principal Components Analysis: Set #2 (Subset of Factors)

Upon rerunning the multivariate regressions with this subset of factors, we find somewhat better results (see Table 5).

Table 5: The table below contains the summarized regression results of running multivariate regressions of the factor subset across each of the ten currencies. The numbers below indicate how many currencies showed significance for each of the factors.

	# Currencies with	
Factor	**p<0.1**	**HAC p<0.1**
Rtns Fac 1	5	5
Rtns Fac 2	9	9
Stdev Fac 1	4	4

Clearly, these look like they have greater predictive power.

4.3.3 Principal Components Analysis: Set #3 (Subset of Factors with Momentum)

We find that momentum is not heavily-weighted across the factors that we have chosen, so we decide to include it separately as a fourth variable in the factor subset. Intuitively, it would make sense that momentum should play a large role since portfolio managers will trade in or out of foreign equities based on whether or not momentum is going in one direction or another. For example, if there is increased momentum this should (hypothetically) lead to portfolio managers selling foreign stocks to buy US stocks, or selling US stocks to buy foreign stocks. Either way, if they trade currencies through the Fix, then this should have an impact on foreign exchange rates within our window. Furthermore, we find statistical support for this since in our univariate regressions, momentum was significant 90% of the time. We add momentum to the factor subset, and then run a multivariate regression across the ten currencies as we did before. The results are shown in Table 6.

Table 6: The table below contains the summarized regression results of running multivariate regressions of the factor subset ***with momentum*** *across each of the ten currencies. The numbers below indicate how many currencies showed significance for each of the factors.*

	# Currencies with	
Factor	**p<0.1**	**HAC p<0.1**
Rtns Fac 1	5	5
Rtns Fac 2	5	5
Stdev Fac 1	4	4
Momentum	5	5

4.4 Stepwise Regressions

Finally, we run stepwise regressions using all 28 variables and allowing for interactions. We choose two criteria for variable elimination across the regressions: 1. minimizing p-values; and 2. minimizing the Akaike Information Criterion (AIC), since we assume that we do not know the true model. .

4.4.1 Minimizing p-Values

Table 7 below shows which variables are chosen by the regression when the p-values are minimized for each currency. Since we allow for interaction terms, and include both returns and standard deviations, it becomes difficult to interpret the results. We leave this as an exercise of imagination for the reader.

4.4.2 Minimizing AIC

Table 8 below shows which variables are chosen by the regression when the p-values are minimized for each currency. Since we allow for interaction terms, and include both returns and standard deviations, it becomes difficult to interpret the results. We leave this as an exercise of imagination for the reader.

Table 7: The results of the stepwise regression across each of the ten currency pairs when minimizing for p-values. An 'x' indicates that that particular variable was chosen for that currency pair. Each variable is numbered and the interaction terms shown below indicate which variables were chosen as interaction terms. Note that for the Australian Dollar (AUDUSD), only the intercept was chosen as giving the minimum p-value none of the independent variables were chosen.

	EURUSD	GBPUSD	USDCHF	USDJPY	USDCAD	AUDUSD	NZDUSD	USDSEK	USDNOK	USDMXN
S&P Rtns										
DAX Rtns										
SSMI Rtns										
Nikkei Rtns										
TSX Rtns										
ASX Rtns										
NZX Rtns				x						
OMX Rtns					x				x	
FTSE Rtns										
IPC Rtns		x								
VIX Rtns										
Div Rtns	x	x		x			x	x		
Term Rtns										
Mom Rtns	x		x	x	x			x	x	x
S&P Stdev				x						
DAX Stdev							x			
SSMI Stdev										
Nikkei Stdev										
TSX Stdev			x							
ASX Stdev										
NZX Stdev				x						x
OMX Stdev										
FTSE Stdev	x	x								
IPC Stdev										
VIX Stdev										
Div Stdev			x							
Term Stdev									x	
Mom Stdev										
Interactions			19x26	7x14						14x21

Table 8: The results of the stepwise regression across each of the ten currency pairs when minimizing for AIC. An 'x' indicates that that particular variable was chosen for that currency pair. Each variable is numbered and the interaction terms shown below indicate which variables were chosen as interaction terms.

	EURUSD	GBPUSD	USDCHF	USDJPY	USDCAD	AUDUSD	NZDUSD	USDSEK	USDNOK	USDMXN
S&P Rtns										
DAX Rtns										
SSMI Rtns	x					x		x		
Nikkei Rtns		x								
TSX Rtns										
ASX Rtns										
NZX Rtns				x						
OMX Rtns					x				x	
FTSE Rtns						x		x		
IPC Rtns		x								
VIX Rtns										
Div Rtns	x	x	x	x		x	x	x		
Term Rtns			x			x	x	x		
Mom Rtns	x	x	x	x	x	x	x	x	x	x
S&P Stdev				x						
DAX Stdev							x			x
SSMI Stdev			x							
Nikkei Stdev					x					
TSX Stdev			x				x			
ASX Stdev										
NZX Stdev	x	x		x	x					x
OMX Stdev										
FTSE Stdev	x	x								
IPC Stdev										
VIX Stdev							x			
Div Stdev			x							
Term Stdev									x	
Mom Stdev							x			
Interactions	12x14	4x12	12x26	7x14		9x13	13x14	3x13		14x21
		12x23	13x14	12x21		12x13		13x14		
			13x26			12x14				
			17x26			13x14				
			12x26							

4.5 Logistic Regression

To summarize, we ran five separate analyses above to get dependent variables on which we will predict and trade based on those predictions. Note that the abbreviations in parentheses are for Table 9.

1. PCA with all relevant factors (PCA1);
2. PCA with factor subset based on multivariate regressions (PCA2);
3. PCA with factor subset and momentum (PCA3);
4. stepwise regression minimizing p-values (Step1); and
5. stepwise regression minimizing AIC (Step2).

Using the variables we retrieved from each of the five analyses above, we test out-of-sample (on 2016 data). We use a logistic regression to predict what each day's foreign exchange returns will be. Since we are focusing on the 10 am to 11 am return, and the logistic regression allows for a categorical (ordinal) variable, we use the following rule:

1. 10 am to 11 am return $> 0 \Rightarrow$ LHS $= 2$
2. 10 am to 11 am return $< 0 \Rightarrow$ LHS $= 1$

This is of course, our left-hand-side LHS variable, and the predictors are based on each of the five techniques outlined above. We pit those five techniques against each other to see which one will give us the highest cumulative annual return. In essence, we train the model on daily data from 2012 through 2015 (inclusive), and then test out-of-sample on 2016 to predict the return, and trade based on that prediction. Our trading rule is simple:

1. Buy, if LHS $= 2$ (10 am to 11 am return > 0);
2. sell, if LHS $= 1$ (10 am to 11 am return < 0).

We use the logit-calculated odds to trade, using a cutoff probability of 50%. In other words, if the probability of the LHS being equal to 1 (based on the RHS predictors) is greater than 50% we **buy** at 10 am and **sell** at 11 am. If the probability is less than 50%, then we **sell** at 10 am and **buy** at 11 am. At present, our data only uses bids, but the liquidity is high in that time-window, and spreads are very low (in the range of 1%). In the future, we will include transactions costs.

Though we have collected data on the logistic regression coefficients, these are not interesting firstly, because they are not interpreted in the same way as a linear regression, and secondly, because we are more interested in the actual results of the trades. So we jump straight to those results.

4.6 Results of Trades

The results of the trades are shown in Table 9. Each currency has a cumulative annual return from trading daily in 2016 based on the probabilities generated by the logistic regression. Predictor variables for each set of trades are chosen based on the models outlined earlier, trained on 2012 - 2015 data.

4.7 Equal-Weighted Portfolios

Finally, we create equal-weighted portfolios across all ten currencies in USD terms. Table 10 has the cumulative annual return for the equal-weighted portfolios, along with their corresponding Sharpe ratios. The table has been sorted by Sharpe ratios, and the cumulative returns are ranked in parentheses.

Ideally, we would like to optimize for Sharpe ratios and use a dynamic model that trains over some period. We would also like to allow for leverage. Both of these are left for further research.

Table 9: The cumulative annual returns from trading daily based on a logistic regression run on 2016 data using predictors from five different models trained in data from 2012 through 2015 (inclusive). The numbers in parentheses are the ranks for each currency performance, with 1 indicating the best performance. The long forms of the abbreviations can be found in Subsection 4.5.

Currency	**PCA1**	**PCA2**	**PCA3**	**Step1**	**Step2**
AUD	4.01% (4)	2.74% (8)	2.65% (6)	N.A.	2.69% (7)
CAD	4.58% (3)	4.17% (1)	4.23% (4)	7.37% (2)	7.69% (2)
CHF	1.98% (7)	2.82% (7)	1.80% (8)	0.35% (7)	0.27% (9)
EUR	0.24% (9)	1.15% (9)	0.93% (9)	-0.12% (8)	1.23% (8)
GBP	6.85% (1)	3.37% (2)	5.78% (3)	4.07% (4)	6.38% (4)
JPY	-3.99% (10)	-2.88% (10)	-2.43% (10)	1.32% (6)	2.89% (6)
MXN	5.45% (2)	3.30% (4)	7.30% (1)	10.09% (1)	10.50% (1)
NOK	2.26% (6)	2.86% (6)	3.59% (5)	5.79% (3)	6.44% (3)
NZD	1.80% (8)	3.34% (3)	6.16% (2)	-1.95% (9)	3.50% (5)
SEK	3.62% (5)	3.25% (5)	2.63% (7)	3.82% (5)	-1.20% (10)

Table 10: The cumulative annual returns, and daily Sharpe ratios from an equal-weighted portfolio across all ten currencies. The values have been sorted by Sharpe ratios and the cumulative annual returns have ranks in parentheses (1 is best).

Technique	**Daily Sharpe**	**Cum. Ret.**
Stepwise Reg (AIC)	0.2158	4.0203% (1)
Stepwise Reg (pVal)	0.1774	3.0435% (3)
PCA All Relevant Factors	0.1207	2.6704% (4)
PCA Subset with Momentum	0.1451	3.2609% (2)
PCA Subset	0.1063	2.4254% (5)

5 Conclusion

In sum, we find that we can indeed exploit this hour-long window in the foreign exchange markets with some success. Whether or not this is repeatable across different years is something we are working on for further research. We are also looking at other statistical techniques grouped under the monicker of 'machine learning' to include in our study to rank and compare against each other.

References

Gino Cenedese, Richard Payne, Lucio Sarno, and Giorgio Valente. What do stock markets tell us about exchange rates? *Review of Finance*, 32:1045–1080, 2016. doi:10.1093/rof/rfv032.

Jim Cochrane. The new wm/reuters fixing methodology doesn't fix everything. ITG Analytics Research Paper, May 2015.

Florian El Mouaaouy. Financial crime "hot spots" – empirical evidence from the foreign exchange market. 32nd Annual Conference of the European Association of Law and Economics 2015, September 2015.

Martin D. D. Evans. Forex trading and the wmr fix. Electronic copy available at: http://ssrn.com/abstract=2487991, November 2014.

H. Hau and H. Rey. Exchange rates, equity prices and capital flows. *Review of Financial Studies*, 19: 273–317, 2006. doi:10.1093/rfs/hhj008.

Takatoshi Ito and Masahiro Yamada. Was the forex fixing fixed? NBER Working Paper No. 21518, September 2015.

Michael Melvin and John Prins. Forecasting exchange rates: An investor perspective. CESIfo Working Paper No. 4238, May 2013.

Michael Melvin and John Prins. Equity hedging and exchange rates at the london 4 p.m. fix. *Journal of Financial Markets*, 22:50–72, 2015.

P. S. Michelberger and J. H. Witte. Foreign exchange market microstructure and the wm/reuters 4pm fix. Electronic copy available at: http://arxiv.org/abs/1501.07778, January 2015.

Pragma Trading. New trading patterns around the wm/r fix. Pragma Research Note, July 2015.