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# Empirical tests of exchange rate and stock return models

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Anna Lindahl

Stockholm, February 2021

## Contents

# Introduction

Previous studies have documented the challenge to explain exchange rate fluctuations with macroeconomic fundamentals. In spite of many years of research, shorter horizons than a year remain difficult to explain and standard macroeconomic models of exchange rates perform poorly particularly out of sample. Meese and Rogoff (1983) compared the forecasting accuracy of several structural and time-series models and established that a random walk model performed as well as any of the estimated models. Typically, regression coefficients would show up with the wrong sign or were not significantly different from zero (Frankel and Rose, 1994). Several studies have subsequently claimed to be successful for a variation of macro variables, exchange rates and time horizons but the positive results have not proved to be robust. On the other hand, studies based on cointegration analysis suggest that there exist a long run equilibrium relation (Mark, 1995; McDonald and Taylor, 1993).

In the late 1990s market micro structure models emerged with focus on the institutional structure and the way information is processed in the foreign exchange market. Compared to traditional models where exchange rates are uniquely and immediately determined by shifts in public macro aggregates, microstructure models attempt to examine how disperse non-public information becomes embedded in the exchange rates through the buy- and sell orders in the trading process. Information contained in individual transactions gets aggregated and conveyed to market makers who may use it in subsequent trading for sharing risk across the market. To the extent that the order flow contain information it will cause an adjustment in the equilibrium exchange rate. Earlier work (e.g., Evans, 2010; King et al., 2010) show that since participants in the foreign exchange market may have different motives to trade and different views of the state of the economy, the information conveyed by order flow to dealers can vary.

The aim of the first chapter of the dissertation, **Order flow in the Foreign Exchange Market**, is to shed light on the short run price dynamics of exchange rates. In particular I seek to understand whether different customer groups act differently in their trading in the euro-sek currency, which leads to different impacts on the exchange rate. As suggested in a sketch of a model by Sager and Taylor (2006), market participants considered to be particularly well informed are expected to initiate price movements whereas other customers, maybe less informed or motivated by technical analysis, are attracted or driven into the market as the price crosses a certain level. To address this question I have collected a rich data set of four years of individual euro-sek transactions starting in January 2001 and ending in December 2004. The detail of my transaction data set allows me to distinguish between different groups of market participants such as Corporate customers, Financial customers and Interbank dealers. In general, order flow data has been, and still is, limited due to confidentiality concerns since the trading activity by major market participants could potentially be identified by competitors. As agreed with the reporting banks, I have therefore eliminated all identities in the data. In the empirical model I regress the euro-sek currency change on different combinations of interest rates and the three order flows; financial, corporate and interdealer banks. Consistent with many earlier studies, the results show that interest rates account for little of the variation in the exchange rate. For aggregate interbank dealer flows, we note correctly signed and significant results which support the view that interdealer flows contain information. However, the framework suggested by Sager and Taylor (2006) where buy orders from financial customers cause an appreciation of the exchange rate is not confirmed in my data. For corporate customers, significant coefficients are found which supports the view that corporate customers act as profit takers and are "pulled" into the market by the price movement first after a change in the exchange rate has been effected by others.

In the second chapter of the thesis, **Herding the Scapegoats: Foreign Exchange Order flow and the Time-Varying Effect of Fundamentals**, we combine the traditional view of macro modelling with the microstructure approach. It has been documented by Sarno and Valente (2009) among others that a possible reason for the low explanatory power in the fundamental-based model is instability in the relationship between exchange rates and macroeconomic fundamentals. In contrast, the microstructure literature shows a link between market participants' order flow and exchange rate dynamics that is remarkably robust. We focus on the question why this is so and build our analysis on a scapegoat theory developed by Bacchetta and van Wincoop (2004, 2013). The central mechanism here is that there is uncertainty about the structural parameters of the economy. When there is no consensus in the market about what causes an exchange rate change, i.e., an unobserved shock, the market searches for an explanation, or "theme", and may attribute it to some observed macro indicator. This macro indicator then becomes a scapegoat, which may influence the trading strategies of the market, and hence order flow. Over time, different macro indicators will be taken as scapegoats so that the weights attributed to the indicators will change. We argue that the stable impact of order flow on the exchange rate exists because order flow incorporates the current "theme" of the market. We attempt at linking the scapegoat theory by Bacchetta and van Wincoop and the order flow theory of exchange rates. We do so by using long runs of monthly inter-dealer order flow on five currency pairs; euro-dollar, dollar-yen, dollar-pound, euro-nok and euro-sek along with data on traditional macroeconomic determinants. Our results suggest that order flow is the channel through which time-varying macro fundamentals work to move the exchange rate. This supports our hypothesis that order flow is the vehicle through which the different opinions of the underlying reasons for changes in the foreign exchange rate get materialized.

In the third chapter of the thesis, **Commerical Banks' Assets and Future**

**expected Returns**, we use information from financial intermediaries' balance sheets to predict asset returns. This is a novel area of research (Adrian et al., 2014; He et al., 2017; Baron and Muir, 2018) within the field of asset predictability in which the behavior of financial intermediaries has a first-order effect on asset prices. We argue that commercial banks' total assets are a more appropriate measure of funding liquidity than broker-dealer book leverage used by Adrian et al. (2014, 2015) because it is a direct measure of credit supply to the whole economy, not only to dealers. Changes in commercial banks' assets are expected to be more connected to economic conditions than broker-dealer book leverage, and thus are expected to have a stronger effect on asset prices. The rationale is that lower asset growth in commercial banks implies lower funding for economic agents, thereby leading to lower consumption and investment. The implied weaker economic conditions lead to higher risk premium. We find that lower asset growth of commercial banks strongly predicts higher excess returns on stocks, bonds, derivatives, and currencies portfolios. This finding is obtained using in-sample and out-of-sample tests while controlling for data mining. Compared to the popular forecasting variables, the bank asset factor is the only one that has positive and significant in-sample and out-of-sample $R^2$, both in recessions and expansions. Bank assets are found to be an important predictor with high frequency data (weekly and monthly) which is a new finding compared to the existing literature on financial intermediaries. Indeed, performing monthly empirical tests with other intermediary asset pricing factors, such as the Adrian et al. (2014) and He et al. (2017) variables, leads to mixed results.

We find that the predictive coefficients on the bank asset factor follow patterns across assets that are consistent with a risk-based explanation. The slope coefficients from the forecasting regressions increase in magnitude from bonds to options to stocks, from high-grade to low-grade bonds, and from big and low book-to-market to small and high book-to-market stocks. This pattern is consistent with the business risks of the assets, and thus supports the risk-based explanation of our results.

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# *Chapter I*

# Order flow in the Foreign Exchange Market*

Anna Lindahl†

**Abstract**

Price discovery in foreign exchange markets is explored using Swedish data including trades from both the customer and the interdealer market. The data set represents a majority of all executed trades in the EURSEK exchange rate over a four-year time period. I confirm the presence of an association between interdealer order flows and exchange rate returns on a daily and weekly frequency. At longer horizons the association disappears. Aggregate interdealer order flow appears to be informed, pushing and driving changes in the EURSEK rate. In contrast, both corporate and financial customers seem to react negatively to a price change and get pulled into the market, reacting to previous trade events.

*Keywords*: Foreign exchange market microstructure; price discovery; private information;

*JEL classification*: F3, F4, G1.

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# 1 Introduction

The literature on foreign exchange market microstructure has emerged to suggest that the quality of traditional fundamental-based exchange rate forecasts in the short run can be improved by incorporating features of the actual foreign exchange trading process. Unlike traditional macro models, the microstructure models see the trading process as central, where relevant information to trading decisions become embedded in the price discovery process via order flow (Evans and Lyons, 2002, 2005; Evans and Rime, 2019). Order flow is defined as the net of buyer-initiated and seller-initiated currency orders submitted to a dealer in foreign exchange. It is a measure of the buying pressure that results from shocks to customers' hedging and liquidity demands and different interpretation of public news.[1]

Lyons (2001) defines private information as information, not known by all, that produces better price forecasts than public information alone. Several studies confirm that price discovery is an important part of the price formation process in asset markets. Hasbrouck (1991), Evans and Lyons (2002a) and Brandt and Kavajecz (2004) document that contemporaneous order flow explains a substantial part of daily price changes in stock markets, foreign exchange markets, and government bond markets, respectively. The fact that order flow adjusts prices gradually reveals that information in the market is not common knowledge as we know it from the standard macro exchange rate models. According to these models new information reach the market symmetrically and prices

[1] Order flow is a measure of the net buying pressure in the market. It is calculated by subtracting seller-initiated trades from buyer-initiated trades during a specific time interval. A buyer-initiated trade will have a positive sign and a seller-initiated trade will have a negative sign.

adjust accordingly without any order flows being exchanged.

The foreign exchange market is characterized by a two-tier structure, reflecting that customers trade with dealers only, while dealers trade both with their customers and with other dealers in the interbank market.[2] The tier where dealers trade with their customers is referred to as the end user market, or customer market, and the tier where dealers trade with other dealers is referred to as the interdealer market. The end user market is heterogeneous since it contains transactions initiated by many different types of traders (e.g. financial agents such as hedge- and investment funds versus non-financial corporations and central banks) with different incentives, reaction speeds to data innovations and risk/return expectations. This makes their order flow an important source of private information (Ito et al., 1998; Bjønnes and Rime, 2005). Dealers may learn and use this private information for their subsequent trades. This assumption is very different from the Kyle (1985) model where dealers are uninformed, only trying to match the net incoming order flow from traders who in turn may be informed or not. Order flow allows the market to learn about the private information and trading strategies of better informed participants, and therefore represents a way for informational asymmetries to become embedded within market prices (Lyons, 1995; Bjønnes and Rime, 2005).

The purpose of this paper is to investigate the role of different market participants in the short run price discovery process of exchange rates. This is interesting since the movements of floating exchange rates are not well understood and raising our knowledge of the market mechanisms may improve our

[2]The trading structure has become more complex in the last decade and customers can now trade on additional venues like single- and multi-bank platforms. For a recent overview of the FX market structure see Evans and Rime (2019).

understanding. Such an understanding requires knowledge of the types of customers prevalent in the market and of the ways in which they trade and interact. Besides, although the actual trading has been facilitated by various electronic trading portals, the transparency of transactions is still low. Compared to the equity market, the lack of disclosure requirements in the foreign exchange market makes much of the trading in this market a black box. The theory of market making predicts that a positive demand shock, i.e., a purchase by the aggressive part in the trade, will lead the market maker to revise prices upwards. Hence, there is a positive contemporaneous correlation between the purchase of the aggressive part and the change of the exchange rate.[3] The supplier of the asset will fill the role of liquidity provider whose net flows will be negatively correlated with the change in the value of the currency.

Previous research using transaction data show that order flow from inter dealer banks and financial customers is positively correlated with exchange rates whereas order flow from commercial customers tends to be negatively correlated. In particular, inter dealer banks and financial customers engage in exchange rate research and from this receive a private signal (information) regarding the actual value of the unobservable fundamental. On the basis of the private as well as publicly available information they submit orders to their FX dealer.

Our results indicate a positive and significant relation between exchange rate movements and net transactions of foreign currency made in the interdealer sector (i.e., for the market making banks) at both daily and weekly frequency. That is, a net purchase leads to a positive change in the exchange rate. This

[3]We denote a purchase by the aggressive part in the trade a positive order flow, while a sale is negative.

relation holds only contemporaneously and not for any lags of order flows. It is somewhat matched by a significant, but negative relation between net purchases of Corporate customers and changes in the exchange rate. Financial customers' order flow is negative and significant, although the results are not as strong as for corporate order flow so the informational impact that financial customers would have according to the theory of market making is not apparent in our study.

Research in the microstructure field using transaction data from different *customer segments* include Bjønnes, Rime and Solheim (2005), Froot and Ramadorai (2005) and Evans and Lyons (2006). Bjønnes, Rime and Solheim (2005) have nine years of aggregated data from the primary dealers of Sveriges Riksbank for Financial as well as non-Financial customers and market making banks in the Euro against Swedish krona. Froot and Ramadorai (2005) have data from the global custodian State Street Corporation, covering foreign exchange transactions in institutional investor funds over a period of seven years in 111 currencies. While the data employed by Froot and Ramadorai (2005) and Evans and Lyons (2006) only represent a small market share of total currency transactions, Bjønnes, Rime and Solheim (2005) and our data reflect almost the entire market activity in EURSEK.[4] However, in contrast to previous studies, the data used in this paper contain information on all individual trades including the identity of all market participants. Our data is totally disaggregated and this allow us to construct specific customer groups and test how these are related to changes in

[4]Bjønnes et al. have data from Sveriges Riksbank. The Riksbank collects daily turnover data from Swedish and a few foreign banks in financial instruments. The classification into financial and non-financial customer were not determined in the data but constructed from an assumption that flows from financial customers have a positive correlation with financial variables like stock indexes and interest rates. Those customers without this correlation were classified as non-financial customers.

the foreign exchange rate. Although the sample period that the data set covers is now somewhat remote, there is still, to the best of our knowledge, no other data set that gives such detailed description on the trading of foreign exchange under such a long period of time.

The rest of the paper is organized as follows. Section 2 describes some of the related literature. Section 3 briefly covers the foreign exchange market and the data. The empirical model used for the regression analysis followed by results are presented in section 4. Finally, section 5 provides a discussion of the results and concludes.

## 2 Related literature

Past work within the microstructure field has mostly focused on interdealer trading since customer transactions are considered confidential and have therefore not been available for research. However, non-dealer customer order flow is central to microstructure theory where it represents the underlying demand for currencies in the real economy and therefore some limited customer data sets have been created. Our study is related to Bjønnes, Rime and Solheim (2005), who investigate whether there is a particular group of market participants that act as liquidity providers overnight. Interdealers are primarily taking the inventory risk intraday but are unwilling to do it overnight. According to microstructure models prices will increase when customers submit buy orders and decrease when they submit sell orders. This may be explained by inventory control models (e.g., Amihud and Mendelson, 1980; Ho and Stoll, 1981) where risk-averse dealers use the price to moderate their inventory of an asset, and information-based models (e.g., Kyle, 1985; Glosten and Milgrom, 1985) with focus on adverse selection where the dealer will adjust prices upward in order to protect himself against a better informed trader. Bjønnes et al. find a negative correlation between the net purchases of foreign currency made by Non-Financial customers and changes in the exchange rate. The negative correlation is matched by a positive correlation between net purchases by Financial customers and changes in the exchange rate.[5] Fan and Lyons (2003) address the trading of FX customers (investors, importers, exporters, corporate treasurers, etc.) at Citibank and find that the different customer categories behave differently with the highest price impact being from financial customers. Fan and Lyons argue that Citibank has relatively many "high-impact customers" who are, on average, better informed.

Although customers order flow are important, there is valid justification for focusing on flow between dealers, the interdealer trading. The justification relates to the differential transparency of customer-dealer versus interdealer flow. Interdealers do observe order flow from interdealer trades including trades in which they are not involved. Customer-dealer trades, on the other hand, are not observable except by the bank that receives them. Dealers therefore learn about other dealers' customer orders as best they can by observing other dealers' interdealer trades, and they set market prices accordingly. The paper by Bjønnes, Osler and Rime (2012) show that large banks have an information advantage, relative to small banks, in the foreign exchange interdealer market. They then

[5]The fact that Bjønnes et al. defined financial customers according to their correlation with financial variables may have contributed to the results for this customer group. The correlation between the Swedish stock index OMX and the Swedish krona has been strong for long periods of time. Hence, if Bjønnes et al. defined financial customers as customers with a strong correlation with the OMX stock index and the OMX stock index has a strong, correctly signed correlation with the EURSEK exchange rate, -0.45, it is not unlikely that the Financial group has a strong "push" effect (Sager and Taylor, 2006) on the EURSEK rate.

trace that advantage to two sources of private information: the larger banks more extensive network of hedge funds and other relatively aggressive financial customers, and the large banks' own ability to generate market insights. The data comprise the complete record of interbank transactions at a big Scandinavian bank during four weeks in 1998 and 1999. They document the information advantage of large banks by comparing average post-trade returns to banks of different sizes. They evaluate the information content of order flow from nine types of customers, using cross-sectional regressions in which the dependent variable is each bank's average post-trade return and the key independent variables are its customer market shares. They find that some customer types do not bring information to the market, namely non-financial corporations, governments, unit trusts, mutual funds, and insurance firms. Information comes from a group of financial customers that includes hedge funds, investment managers, pension funds, and non-dealing banks. Bjønnes et al. also suggest that currency banks bring their own information to the market. This is in contrast to the literature which uniformly assumes that all private information in currency markets originates with end users. Their findings are in accordance with Valseth (2013) who investigates the price impact of interdealer order flow relative to customer order flow. The results show that aggregate interdealer order flow contains information while aggregate customer flow does not. It can be because dealers are skilled and collect information while customers do not, but it can also be because the trades of informed customers are not reflected in aggregate customer order flow. In order to find out which is the case she employs a proxy for informed customer order flow by identifying so called delayed publication trades. These are trades chosen by dealers to be hidden temporarily from the other dealers in the market. Dealers are likely to choose this alternative if the trades contain private information that may be exploited first, before the trade is registered. Delayed publication customer trades are therefore used as a proxy for informed customer trades. The results show that inter dealer order flow in the Norwegian bond market explains 25% of daily yield changes whereas aggregate customer trades explain up to 1% of daily variation in yields. The differences in the explanatory power of interdealer order flow and customer order flow suggest that dealers are better informed than their customers.

Likewise, Osler and Vandrovych (2009), with a data set of foreign exchange transactions from Royal bank of Scotland, report that order flow generated by leveraged investors, such as hedge funds and banks, have a strong and lasting impact on the exchange rate whereas order flow from unleveraged institutional investors, large corporations, government agencies, and central banks appears to convey little private information. They also suggest that banks are better informed than their individual customers, possibly because they aggregate information from many customers.

Our study is related to all of the above mentioned papers. Instead of examining either the interdealer market, like Bjønnes, Osler and Rime (2012), Valseth (2013) or the customer market, like Fan and Lyons (2003) and Bjønnes, Rime and Solheim (2005), the analysis in this paper studies both and can therefore examine the relationship between the two parts. Osler and Vandrovych (2009) also include both the interdealer and customer markets, but only for one bank.

# 3 Market structure and data

The foreign exchange market is decentralized in the sense that market participants are generally separated from one another and transactions take place through various trading platforms. The first implication of decentralization is that the market is fragmented in the sense that transactions occur simultaneously at similar prices. The second is that it is opaque, lacks transparency in the sense that the absence of a physical marketplace makes the process of price-formation interaction difficult to observe and understand. Moreover, the foreign exchange market is the most liquid market in the world. According to the BIS Triennial Survey the daily average foreign exchange turnover increased in 2001 from approximately \$1.2 to \$1.9 trillions in 2004.[6] Swap transactions have the highest daily turnover in all foreign exchange markets with 53% of total trades. Spot transactions amount to 35% and the remaining 12 % are outright forwards. According to the BIS survey, 48% of the total turnover of spot trades are interdealer transactions, which is close to the share of 54% for our data set. The transactions with financial customers amounts to 34% in the BIS survey and 32% for our data. Finally, trading with non-financial customers has a market share of 17% in the BIS survey and 14% in our data. Foreign exchange market structure and participant group interactions have changed substantially since the beginning of the 21st century in most currencies, including the EURSEK rate, and most of the increase in turnover comes from the various customer groups in the market.[7] The motivation for these flows has also changed in the sense that investors increasingly see the foreign exchange market as a potential source that can pro-

[6]Net-net basis. In 2016 the total daily turnover had increased to \$5.1 trillions.

[7]Customer here includes asset management firms, hedge funds, commodity trading advisors (CTAs), central banks, corporations and high net worth private individuals.

vide important diversification benefits when combined in a portfolio of other assets. The turnover in SEK against other currencies has been fairly constant at two percent of the total foreign exchange market from 2001 and onwards.

The foreign exchange market is structured as a two-tier market, where end-users of currency (households and firms) transact with intermediaries (banks) in the first tier, then the intermediaries transact with each other (Interdealer) in the second tier. The intermediaries have either self-imposed limits or regulated limits on how much currency to hold overnight and cannot be expected to take lasting open positions. Hence, intermediaries provide liquidity intraday but are less likely to provide liquidity over longer horizons. In this sense they are truly intermediating the currency transactions by the firms and households.

Our data sample covers the period January 2001 to December 2004 and consist of spot exchange transactions in EURSEK executed by seven major market making banks in the SEK currency. Compared to previous end-user data sets as in Marsh and O'Rourke (2005), Evans and Lyons (2005), Bjønnes et al. (2005) or Evans and Lyons (2007) e.g., this data set is more complete in that it has a very high coverage of both customer and interdealer transactions. Since customer data is considered highly confidential, most previous studies of exchange rates and order flow have used interbank data only. According to the agreement with the reporting banks, the identity of banks and counterparties will not be revealed in the study. While the major currencies USD, EUR and JPY are traded world wide the SEK is traded mostly locally by a limited number of market making banks, which facilitates the collection of data. In order to avoid a large number of very small orders we have excluded order sizes below 100000 EUR. The data set is unusually rich in features, since it includes information on counterparty names, volume and execution price of transactions, who sells and who buys, and the exact time of transaction. Previous data sets are usually aggregated and filtered in some way by the data supplier in order to protect the customer identities from being revealed. In contrast, our data are collected and treated by ourselves, which means that we have control of the entire sequence.

Since the time of our sample, the FX market has evolved and new trading systems have changed the transaction structure. Algorithmic and high-frequency trading has increased and the relative importance of market and limit orders has changed the nature of price discovery (Chaboud, Hjalmarsson and Zikes, 2018). Very large and active hedge funds have now direct access to the inter-dealer market. However, the basic structure and the underlying reasons most agents trade currencies have not changed. Financial customers continue to rely on currencies as a value-enhancing asset and therefore still have an incentive to gather information; Non-financial customers continue to use currencies primarily as a medium of exchange so their incentive to gather information is relatively limited. Dealers continue to provide liquidity and bear inventory risk, and thus still have a strong incentive to gather information from customers (Osler, Mende and Menkhoff, 2011).

According to microstructure theory, different customers may have diverse information regarding the state of the macroeconomy and they may have different motives for trading currencies (Evans, 2017). This means that dealers can receive order flow containing information that varies according to the end-user counterparty in each transaction. With our data we are able to examine the differences in the information expressed by order flows to the extent that it is reflected in the behavior of spot rates. Marsh and O'Rourke (2005) and Evans and Lyons

(2005) find that the main differences in the response of spot rates to order flows from different customer groups appear between the flows of financial and non-financial end-users. Our data contain all identities of the counterparties in each trade but in line with the findings in the above mentioned studies, we decided to group these into the purchases and sales of three types of trades: Financial, Corporates and Interdealers. Specifically, the financial group consist of hedge funds, insurance companies, asset management funds, pension funds, brokerage firms, trust funds and treasury departments. Corporates would typically include export companies whose primary interest refers to making profits from selling goods in the world market, not speculating in foreign exchange. Financial customers on the other hand are more likely to treat the foreign currency as an asset yielding a potential profit. Interdealers act as intermediaries rendering exchange services to other market participants, i.e., not trading for their own account, but also have skills in interpreting relevant information that they subsequently trade on in order to make a profit.

Following previous studies (e.g. Love and Payne, 2008) we define order flow as the difference between the volume of buyer-initiated trades and seller-initiated trades, measured in the base currency. It is hence a measure of net buying pressure. A buyer-initiated trade is a transaction where a dealer at a bank places a quote offering to sell Euro for kronor (for example) in an electronic limit order book. This is dealt on by another dealer or a trader, who buys the EUR and thus is considered the agressor, or the initiator of the transaction. A seller initiated trade is, of course, analogously defined. Order flow is a measure of signed transaction flow: Trades initiated by the buyer are positive order flow and trades initiated by the seller are negative order flow. The trades in our dataset are signed as buyer-initiated or seller-initiated by the reporting banks, so we do not have to rely on an algorithm to estimate the direction of trade. The transactions during a given day are aggregated from 8:00 to 16:00, Stockholm time, in order to get daily values. Weekly values are obtained by aggregating over Monday to Friday every week. The change in the spot rate EURSEK is the log change in the exchange rate between 4pm on day t and 4pm on day t-1[8]. Our exchange rate data denote the amount of Swedish kronor required to buy one Euro.

[Figure 1 about here.]

Panel 1A in Figure 1 shows the exchange rate during the relevant time period. The data covers a period during which the EURSEK was rather stable with the exception of a large movement in the beginning of the period. The daily standard deviation is only 0.4 percent for the four years we study. Panel B to D show the cumulative order flows for each counterparty group.

[Table 1 about here.]

Table 1 reports some summary statistics for the daily and weekly exchange rate, order flow and macro data. Along the lines of the seminal paper by Evans and Lyons (2002a) and Evans and Rime (2016) we add two macro variables, available daily, to represent public information in macro models; the difference in short rate interest rates and the yield curve differential for EUR and SEK.[9] The table shows the mean, median, max and min, standard deviation as well as

[8] World market rate, mid 4pm fix

[9] We refer to IDIFF as the difference between three month Treasury bill rate in EUR and SEK. We refer to ISLOPEDIFF as the yield curve differential where we take the difference between the five year bond rate and the three month Treasury bill rate for EUR and SEK respectively and then use the difference between them.

first and second order autocorrelation. Financial order flow (FIN) is only serially correlated at the weekly horizon and interdealer order flows (BANK) are serially correlated at both the daily and weekly horizon. The estimated autocorrelation coefficients are quite small, but positive and statistically significant. We see that interdealer flows are much more volatile than any of the customer flows and that financial flows are more volatile than corporate flows. All flows seem to be skewed to the left.

[Table 2 about here.]

Table 2 shows the correlations between the different order flows and some macro variables at the daily frequency. Correlations are mostly not significant and very low with the exception of the interest rate variables. Noteworthy is the very low correlation between the EURSEK exchange rate change and order flows where the coefficient on interdealer flows is the highest, positive and significant. The correlation between the change in the Swedish stock index OMX and the EURSEK rate is -0.33 and significant at the 1% level implying a stronger SEK when the Swedish stock market return increases. Weekly values give slightly higher correlations but interdealer flows turn negative in accordance with the rest of the flows.

# 4 Informed order flow

In microstructure finance models order flow conveys information that needs to be aggregated to be regarded as a proximate determinant of price. The information may include anything that can have an impact on the demand for the currency (different interpretations of news, shocks to hedging demands and shocks to liquidity demands) so long as that information is not common knowledge in the market. Common knowledge, as we know it from the macro exchange rate models, is defined as new information which reaches the market symmetrically and with prices adjusting accordingly without any order flows being exchanged. If we assume the additional existence of private information as well, order flow becomes the intermediate link between new information and price - a proximate cause of price movements (Evans and Lyons, 2002a).

As discussed in section 3 the customer order flow data sets available for academic research are few. Ours cover a longer period, four years, and is more detailed than most other data sets. Following the empirical analysis by Marsh and O'Rourke (2005) we first establish that there is a correlation between customer flows and exchange rates in our data using the following simple regression:

$$\log(s_t) - \log(s_{t-1}) = \alpha + \beta_1(OF_{fin,t} + OF_{corp,t}) + u_t \tag{1}$$

The dependent variable is the change in the log of the spot exchange rate and the single independent variable is the aggregated customer order flow, containing the aggregate net order flows of financial and corporate customers but without interdealer order flows. A positive $\beta$ would suggest that order flow into a currency - the net buying pressure - is related to an appreciation of the currency.

[Table 3 about here.]

Table 3 reports the OLS estimation of equation (1) at one-day and one-week horizons for EURSEK. At both frequencies we use heteroscedasticity robust standard errors. The results show that financial and corporate flows together have a significant, but negative, price impact at the 5% level for the daily horizon and at the 1% level for the weekly horizon. The $R^2$ is around 0.5% for the daily and 4.5% for the weekly horizons.

## 4.1 Disaggregated order flow and exchange rate change

The regression in equation (1) above made the assumption that the impact of the net order flow on the exchange rate is equal for all customer types. If the correlation between the exchange rate and order flow is due to liquidity effects this may be reasonable because then the nature of the counterparty should be irrelevant and the market maker should set his price equally for a trade of equal size whether it is from a corporate or financial customer. However, if the order flow is due to private information the constraint may not be appropriate. It is then possible that some types of customers are more informed than others. The papers of Fan and Lyons (2003) and Carpenter and Wang (2007) discuss and find evidence that in FX markets, transactions initiated by financial customers convey more information, at least in the short run, than do transactions initiated by commercial customers. The constraint from equation (1) is relaxed in equation (2) and the exchange rate is regressed on disaggregated net order flows as well as interest rate differentials.

$$\begin{aligned} \log(s_t) - \log(s_{t-1}) = \alpha + \beta_1 OF_{fin,t} + \beta_2 OF_{bank,t} + \beta_3 OF_{corp,t} \\ + \beta_4 didiff_t + \beta_5 dislopediff_t + u_t \end{aligned} \tag{2}$$

[Table 4 about here.]

[Table 5 about here.]

Tables 4 and 5 show the results from estimating equation (2), with and without the interest rate variables included, respectively. Consistent with many earlier studies, we find that the interest rates account for little of the variation in the exchange rate. None of the interest rate coefficients are significant at conventional levels at the daily or weekly horizons and the $R^2$s of the regressions change only marginally with the inclusion of the interest rate variables.

[Table 6 about here.]

The $R^2$s for models with only interest rate variables are essentially zero as shown in the model specification I in table 6. In contrast, Tables 4 and 5 show that all order flow variables are significant at the five percent level. These results are summarized in table 6 where we present the results from regressing the EURSEK exchange rate change on different combinations of interest rates and the three order flows; financial, corporate and interdealer banks as defined above. The dependent variable in these regressions is the one-day and one-week change in the log exchange rate. Heteroscedastic-robust t-values are reported in parentheses below the coefficient estimates.

According to Bjønnes and Rime (2005); Sager and Taylor (2006), the financial customers' buy orders may coincide with appreciations of the currency. Financial customers are analysing the currency market continuously and by placing orders by either electronic platforms or directly through a dealer at a market making bank they may supply the market with information that is not yet common knowledge. Hence, in equation (2) above we could expect the coefficient $\beta_1$ for financial order flow to be positive. However, the estimates in Tables 4 - 6 show that the coefficients on financial and corporate order flows are significant and negative; a net purchase of EURSEK would result in a weakening of the currency at both daily and weekly horizons. The impact from corporate customers is in accordance with the market microstructure hypothesis. Acting in response to an exchange rate movement, the expected sign is negative. The results thus support our view that corporate customers are "pulled" into the market following a change in the exchange rate, possibly caused by some other customer group. Our order flows are only weakly correlated. Financial and interdealer flows have the highest correlation of 0.2, statistically significant.

Regarding interbank dealer flows, we note correctly signed (i.e., positive) and (highly) significant results. Trading in the interbank segment is characterized by a large number of dealers who can buy or sell foreign currency to customers and other dealers. Customer orders are only observed by the recipient dealer and so may represent a source of private information to the dealer. Dealers then quote prices and trade in the interdealer market. The disclosure requirement of trades in this segment makes this market more transparent and information is dispersed quickly. In this sense, interdealer order flow is considered as semi-public information. Compared to customer trades, interdealer trades are the most observable and thus easiest for the market to condition on in order to set prices. We may think about the interdealer flows as characterized by a very large turnover with high volatility, absorbing and digesting new information very actively, hence learning fast. The main advantage should be the fact that dealers are located in the aggregated flow of trades. This makes it possible for them to extract a signal about the demand and direction of the exchange rate. Dealers may also obtain extra information by using effort and skill in collecting and interpreting other relevant information. In this case dealer skill is a source of information. Anand and Subrahmanyam (2008) find that dealers contribute more to price discovery than their customers and conclude that dealers are better informed than other market participants. Given their high activity, interdealer flows are expected to affect the exchange rate contemporaneously. Previous order flows are less likely to have an impact since it continuously gets replaced by order flows containing new information.

On the contrary, corporate flows are assumed to originate from international trade of goods and services and as such show less variation and would need longer to learn about new information relevant for the exchange rate. Financial flows are assumed to be found in between the two.

The economic significance of the estimated model in table 4 is that a net flow of 1 million into the Euro from corporate customers is associated with 0.079 basis points (0.00079%) depreciation of the Euro daily and 0.169 basis points (0.00169%) weekly. A similar net flow from interdealers is associated with 0.041 basis points (0.00041%) rise in the value of the Euro over one day and 0.032 basis points (0.00032%) over a week. Hence, the corporate order flow has a larger effect on both daily and weekly return changes. The adjusted explanatory power $R^2$ for the regression model (2) is 7.6% at the daily frequency and 13.6% at the weekly frequency.

## 4.2 Robustness

The coefficient on financial flows in the OLS regressions are in fact negative and significant at the 5% significance level. Interdealer flows and corporate flows are (strongly) significant at 1% significance level. These results show that aggregate interdealer flows have information relevant for future returns and play a role in the price formation process. Corporate customers act as profit takers, reacting to a change in the exchange rate, with a negative coefficient. Put differently, corporate customers follow negative feedback rules in that they buy the currency that has just depreciated. Conversations with dealers and foreign exchange sales employees in banks reveal that corporates take advantage of short-term exchange rate changes to exchange money for non-speculative reasons (e.g repatriation of funds; Marsh and O'Rourke, 2005). Since the sign is negative on both corporate and financial flows, negative feedback trading could of course also hold for the latter. However, given our assumption that financial customers are more informed it seems irrational by them to react to an exchange rate movement instead of using their superior information to take active positions. By regressing interdealer order flow on corporate and financial order flow we note a non-significant relation with corporate order flow and a positive and significant coefficient for financial order flow. Hence, although the direct impact from financial order flow on the exchange rate is negative, interdealers seem to find the financial flows somewhat informative for future trading. In this way there is an indirect impact from financial customers flow on the exchange rate. It is possible to think of a situation where financial customers are informed only so much such that their order flow has a positive impact on interdealer order flow but no impact on the exchange rate directly. The reason for this could be that financial flow only affect the "non-informative" part of dealer flow i.e., the part that does not correlate with changes in the exchange rate, or that dealers in some way uses the information of financial flows without financial customers actually receiving any benefit from it.

We examine the robustness of our results by estimating a VAR model in order to check whether there are lead-lag relationships for the three different types of order flows and the exchange rate. As exogenous variables we use the two interest rate variables IDIFF and ISLOPEDIFF. The lag order for the endogenous variables are five for the daily and one for the weekly VAR model.

[Figure 2 about here.]

In figure 2 we show the cumulative impulse responses of the exchange rate in the VAR to a one standard deviation shock to each of the order flow variables. The responses are estimated and plotted for each pair of shock and exchange rate over ten periods. In both daily and weekly figures we have estimated a VAR with financial order flow first, interdealer flow second, corporate flow third and the change in the EURSEK rate as the last.[10] The two interest variables idiff and islopediff are considered as exogenous. The cumulative responses indicate that the effects of the different shocks are permanent as the initial effects are not reverted. The red lines describe the confidence intervals of our estimates and we note that the intervals for financial customers include zero in both the daily and weekly cases. Hence, in contrast to the OLS-results we can conclude that the IRF for financial customers is not significantly different from zero. On the other hand, a shock to inter dealer flows generates a positive effect on the exchange rate whereas a shock in corporate flows affects the exchange rate negatively, both significantly. Based on the VAR model, the result for financial customers seems less robust than those for corporate customers and inter dealing banks; for the latter two, the VAR and the OLS regressions deliver the same qualitative conclusions. However, the VAR puts considerably greater demands on the data

[10]Modifying the ordering of the endogenous variables do not change the reactions.

and estimates many more coefficients than the simple OLS regressions, and one should not simply disregard the OLS results. To the extent one believes that the financial flows has *some* impact on the exchange rate, the OLS results strongly suggest that it is negative, but the VAR arguably puts some doubts on whether this impact is permanent or merely transitory.

# 5 Conclusion

So far there is little evidence that standard macroeconomic models of exchange rates have anything to say about short term movements other than the impact of news announcements. There has been a growing literature that suggests the microstructure approach has something more positive to contribute. In general, there is a broad consensus that order flow is the central mechanism by which private information is carried over to exchange rates. In this paper we have addressed the question whether different market participants act differently in their trading in EURSEK, which leads to different impacts on the exchange rate. The conclusion from our study is that overall, the change in the EURSEK exchange rate is difficult to explain on the basis of the information contained in the set of customer order flows. The results are not strongly suggestive of any significant "push effect" of customer order flow on the variation of the foreign exchange return. The framework suggested by Sager and Taylor (2006) where financial customers push the exchange rate can not be confirmed in our data. Instead, our results confirm the more recent results in the Microstructure literature that interdealer order flow contains information while customer order flow does not. Buy orders from financial customers do not cause an appreciation of the currency whereas interdealer flows do. For corporate customers, significant coefficients are found at the daily and monthly horizon. This supports the view that corporate customers are "pulled" into the market by the price movement first after a change in the exchange rate has been effected by others. In this respect they act as liquidity providers since they enter the market in a reaction to the action of others. So, despite the established view that customer order flow is considered to be the vehicle incorporating non-public information into exchange rates, our analysis rather support the view that interdealer flows contain information. Being at the centre of large trading volumes and having access to skills in treating and interpreting economic data provide interdealers with an advantage.

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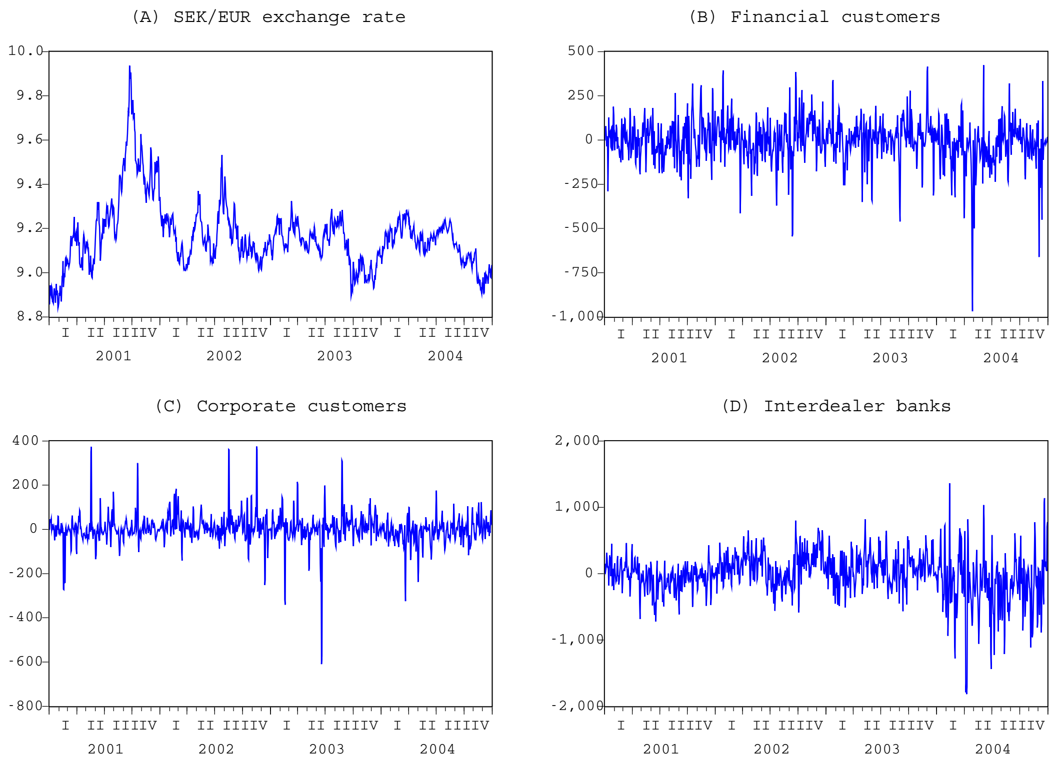
# Figure 1
# EURSEK and cumulative order flow series




Note: The Figure show four years of the EURSEK exchange rate and cumulative order flows for financial, corporate and interdealer market participants. Millions of Euro. Source: World Market Rate, Thomson Reuters Data. Sample period: January 2001 – December 2004.

## Table 1
## Descriptive Statistics

DAILY

| | $\Delta s_t$ | BANK | CORP | FIN | IDIFF | ISLOPED |
|---|---|---|---|---|---|---|
| Mean | 0.003 | -5.380 | 1.428 | -3.233 | 0.418 | 0.252 |
| Median | 0.008 | 0.000 | 0.000 | 0.000 | 0.520 | 0.170 |
| Maximum | 1.904 | 1190.036 | 372.308 | 423.804 | 1.210 | 1.070 |
| Minimum | -1.753 | -1718.714 | -596.260 | -618.670 | -0.830 | -0.435 |
| Std. Dev. | 0.004 | 221.315 | 48.613 | 89.201 | 0.534 | 0.366 |
| Skewness | -0.058 | -1.131 | -0.937 | -0.742 | -0.488 | 0.248 |
| Kurtosis | 5.267 | 12.826 | 40.209 | 9.609 | 2.254 | 1.741 |
| AC(1) | 0.037 | 0.110 | 0.040 | 0.006 | 0.929 | 0.913 |
| *Prob.* | *0.234* | *0.000* | *0.220* | *0.834* | *0.000* | *0.000* |
| AC(2) | 0.074 | 0.140 | 0.030 | 0.045 | 0.911 | 0.904 |
| *Prob.* | *0.029* | *0.000* | *0.279* | *0.344* | *0.000* | *0.000* |
| Jarque-Bera | 224.360 | 4426.347 | 60436.840 | 1997.850 | 65.734 | 79.749 |
| *Probability* | *0.000* | *0.000* | *0.000* | *0.000* | *0.000* | *0.000* |
| Sum | 0.027 | -5621.876 | 1492.249 | -3378.881 | 436.860 | 263.646 |
| Sum Sq. Dev. | 0.015 | 51135549 | 2467224 | 8306828 | 297.612 | 139.952 |
| Observations | 1045 | 1045 | 1045 | 1045 | 1045 | 1045 |

WEEKLY

| | $\Delta s_t$ | BANK | CORP | FIN | IDIFF | ISLOPED |
|---|---|---|---|---|---|---|
| Mean | 0.000 | -28.849 | 6.779 | -16.456 | 0.422 | 0.244 |
| Median | 0.001 | 36.972 | 3.147 | -1.587 | 0.520 | 0.150 |
| Maximum | 0.032 | 1208.780 | 492.206 | 494.612 | 1.150 | 0.943 |
| Minimum | -0.025 | -3599.683 | -660.331 | -1072.593 | -0.790 | -0.350 |
| Std. Dev. | 0.008 | 624.455 | 116.434 | 203.283 | 0.526 | 0.360 |
| Skewness | -0.037 | -1.249 | -0.304 | -0.878 | -0.485 | 0.297 |
| Kurtosis | 4.434 | 7.790 | 9.905 | 6.299 | 2.262 | 1.716 |
| AC(1) | -0.160 | 0.265 | 0.103 | 0.233 | 0.882 | 0.868 |
| *Prob.* | *0.020* | *0.000* | *0.135* | *0.001* | *0.000* | *0.000* |
| AC(2) | 0.040 | 0.254 | -0.008 | 0.136 | 0.859 | 0.851 |
| *Prob.* | *0.057* | *0.000* | *0.324* | *0.000* | *0.000* | *0.000* |
| Jarque-Bera | 17.860 | 252.885 | 416.388 | 121.033 | 12.873 | 17.347 |
| *Probability* | *0.000* | *0.000* | *0.000* | *0.000* | *0.002* | *0.000* |
| Sum | 0.015 | -6000.661 | 1409.979 | -3422.836 | 87.850 | 50.823 |
| Sum Sq. Dev. | 0.012 | 80718468 | 2806257 | 8554065 | 57.351 | 26.775 |
| Observations | 208 | 208 | 208 | 208 | 208 | 208 |

Note: The table shows descriptive statistics for daily and weekly observations of order flows for the EURSEK exchange rate change, financials (FIN), corporates (CORP) and interbank dealers (BANK). IDIFF is the difference in three month EUR and SEK Treasury bill rates and ISLOPED is the interest rate differential of the EUR and SEK yield curve slopes. The EURSEK exchange rate change $\Delta s$ is calculated as the daily and weekly change in the natural log of the spot price (EURSEK) x 100. The order flows are daily and weekly aggregates for the SEK in millions of EUR. Sample period: Jan. 2001 – Dec. 2004.

## Table 2
## Correlation coefficients

| Correlation | BANK | FIN | CORP | $\Delta s_t$ | IDIFF | ISLOPEDIFF | D(OMX) |
|---|---|---|---|---|---|---|---|
| BANK | 1 | | | | | | |
| FIN | 0.20<br>(0.00) | 1 | | | | | |
| CORP | 0.05<br>(0.12) | 0.08<br>(0.02) | 1 | | | | |
| $\Delta s_t$ | 0.23<br>(0.00) | -0.03<br>(0.30) | -0.10<br>(0.00) | 1 | | | |
| IDIFF | 0.18<br>(0.00) | 0.04<br>(0.18) | 0.06<br>(0.05) | -0.01<br>(0.70) | 1 | | |
| ISLOPEDIFF | -0.21<br>(0.00) | -0.05<br>(0.16) | -0.04<br>(0.22) | 0.00<br>(0.89) | -0.92<br>(0.00) | 1 | |
| D(OMX) | -0.07<br>(0.02) | 0.00<br>(0.88) | 0.04<br>(0.22) | -0.33<br>(0.00) | 0.02<br>(0.58) | 0.00<br>(0.92) | 1 |

Note: This table shows the unconditional correlations between the EURSEK log exchange rate rate $\Delta s$, volumes of order flows, interest rate differentials and the Swedish stock index (OMX). The change in the foreign exchange rate is daily change in the EURSEK rate. Numbers in parentheses are p-values. Sample period: Jan. 2001 – Dec. 2004.

## Table 3
## Customer order flow regressions

| Variable | Coefficient ($\times 10^4$) | Std. Error ($\times 10^5$) | t-Statistic | p-value |
|---|---|---|---|---|
| **Daily** | | | | |
| C | 0.140 | 10.300 | 0.136 | 0.892 |
| FIN+CORP | -0.026 | 0.119 | -2.135 | **0.033** |
| $R^2$ | 0.006 | | | |
| **Weekly** | | | | |
| C | 0.099 | 43.810 | 0.023 | 0.982 |
| FIN+CORP | -0.065 | 0.206 | -3.148 | **0.002** |
| $R^2$ | 0.045 | | | |

Note: The table reports OLS estimates, $t$-statistics and $R^2$ of the coefficients from regressions of the log exchange rate $\Delta s$ on aggregate net customer order flow $FIN + CORP$. Estimates are computed over the daily and weekly horizon. Bold p-values denote coefficients significant at the 5% level. Sample period: Jan. 2001 – Dec. 2004.

# Table 4
# Disaggregated order flow regressions

| Variable | Coefficient ($\times 10^4$) | Std. Error ($\times 10^5$) | t-Statistic | p-value |
|---|---|---|---|---|
| **Daily** | | | | |
| C | 0.435 | 10.000 | 0.434 | 0.664 |
| BANK | 0.041 | 0.069 | 5.964 | **0.000** |
| FIN | -0.030 | 0.142 | -2.070 | **0.039** |
| CORP | -0.079 | 0.279 | -2.810 | **0.005** |
| D(IDIFF) | -0.001 | 43.600 | -1.859 | 0.063 |
| D(ISLOPEDIFF) | 0.001 | 65.600 | 0.862 | 0.389 |
| $R^2$ | 0.076 | | | |
| **Weekly** | | | | |
| C | 1.980 | 44.000 | 0.450 | 0.653 |
| BANK | 0.032 | 0.061 | 5.245 | **0.000** |
| FIN | -0.053 | 0.210 | -2.521 | **0.013** |
| CORP | -0.169 | 0.471 | -3.583 | **0.000** |
| D(IDIFF) | 14.920 | 218.300 | 0.684 | 0.495 |
| D(ISLOPEDIFF) | 28.150 | 244.500 | 1.151 | 0.251 |
| $R^2$ | 0.136 | | | |

Note: The table reports OLS estimates, $t$-statistics and $R^2$ of the coefficients from regressions of the form: $\log(s_t) - \log(s_{t-1}) = \alpha + \beta_1 OF_{fin,t} + \beta_2 OF_{bank,t} + \beta_3 OF_{corp,t} + \beta_4 didiff_t + \beta_5 dislopediff_t + u_t$. The dependent variable is the log exchange rate $\Delta s$ over the daily and weekly interval. The explanatory variables are interest rates and net order flows for financial, interdealer and corporate customers. Bold p-values denote coefficients significant at the 5% level. Sample period: Jan. 2001 – Dec. 2004.

# Table 5
# Disaggregated order flow regressions, no interest rates

| Variable | Coefficient ($\times 10^4$) | Std. Error ($\times 10^5$) | t-Statistic | p-value |
|---|---|---|---|---|
| **Daily** | | | | |
| C | 0.421 | 10.000 | 0.420 | 0.675 |
| BANK | 0.041 | 0.069 | 5.964 | **0.000** |
| FIN | -0.030 | 0.142 | -2.129 | **0.034** |
| CORP | -0.078 | 0.279 | -2.812 | **0.005** |
| $R^2$ | 0.072 | | | |
| **Weekly** | | | | |
| C | 1.890 | 44.200 | 0.427 | 0.670 |
| BANK | 0.032 | 0.059 | 5.495 | **0.000** |
| FIN | -0.054 | 0.205 | -2.614 | **0.010** |
| CORP | -0.164 | 0.499 | -3.276 | **0.001** |
| $R^2$ | 0.132 | | | |

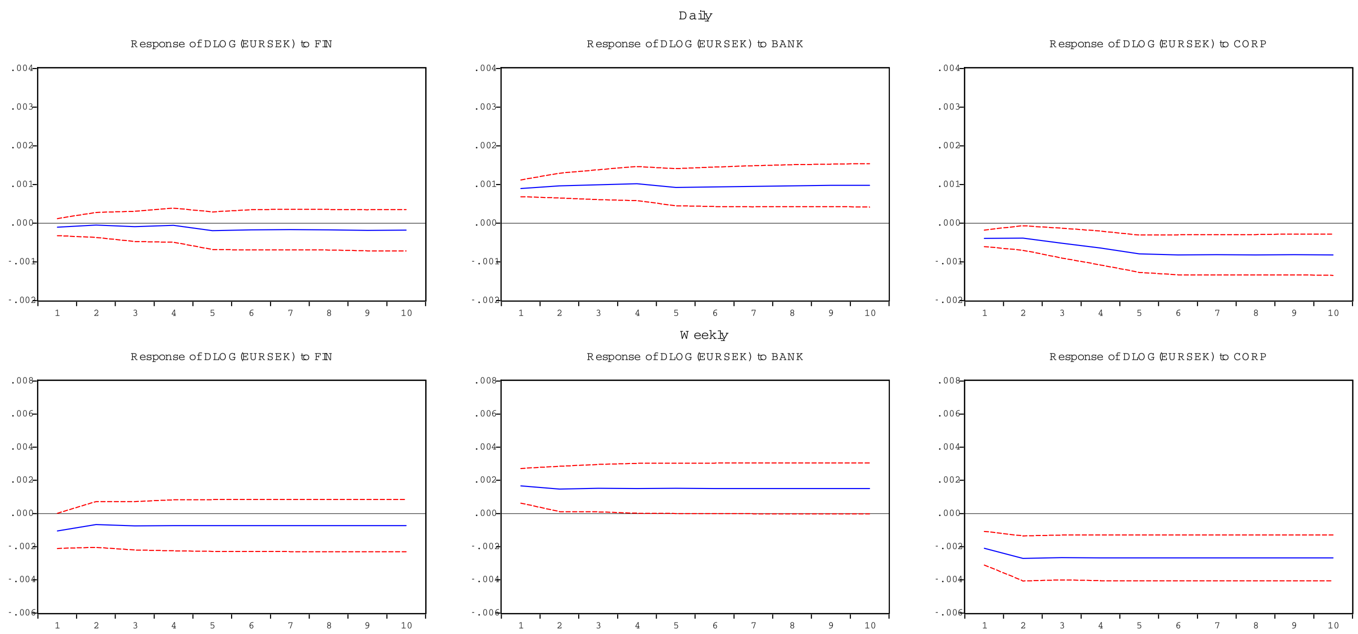
Note: The table reports OLS estimates, $t$-statistics and $R^2$ of the coefficients from regressions of the form: $\log(s_t) - \log(s_{t-1}) = \alpha + \beta_1 OF_{fin,t} + \beta_2 OF_{bank,t} + \beta_3 OF_{corp,t} + u_t$. The dependent variable is the log exchange rate $\Delta s$ over the daily and weekly interval. The explanatory variables are interest rates and net order flows for financial, interdealer and corporate customers. Bold p-values denote coefficients significant at the 5% level. Sample period: Jan. 2001 – Dec. 2004.

## Table 6
## Model estimates

| Specification | didiff | dislopediff | FIN | CORP | BANK | $R^2$ |
|---|---|---|---|---|---|---|
| | | | Daily | | | |
| I | -7.060 | 5.000 | | | | 0.003 |
| t-stat | (-1.484) | (-0.742) | | | | |
| II | | | -0.013 | | | 0.001 |
| t-stat | | | (-0.930) | | | |
| III | | | | -0.074 | | 0.010 |
| t-stat | | | | (-2.640) | | |
| IV | | | | | 0.0376 | 0.054 |
| t-stat | | | | | (-5.647) | |
| V | -8.110 | 5.650 | -0.030 | -0.079 | 0.041 | 0.076 |
| t-stat | (-1.859) | (-0.862) | (-2.070) | (-2.810) | (-5.964) | |
| | | | Weekly | | | |
| I | 23.530 | 5.820 | | | | 0.003 |
| t-stat | (-0.805) | (-0.290) | | | | |
| II | | | -0.046 | | | 0.014 |
| t-stat | | | (-2.187) | | | |
| III | | | | -0.169 | | 0.064 |
| t-stat | | | | (-3.275) | | |
| IV | | | | | 0.025 | 0.042 |
| t-stat | | | | | (-4.174) | |
| V | 14.920 | 28.150 | -0.053 | -0.169 | 0.032 | 0.136 |
| t-stat | (-0.684) | (-1.151) | (-2.521) | (-3.583) | (-5.245) | |

Note: The table reports OLS estimates, $t$-statistics and $R^2$ of the coefficients from regressions of the dependent variable log exchange rate $\Delta s$ on daily and weekly interest rates (specification I), financial order flow alone (specification II), corporate order flow alone (specification III), interdealer order flow alone (specification IV) and all variables together (specification V). The dependent variable $\Delta s$ is the change in the log spot EURSEK from 16.00 on day $t-1$ to day $t$. All coefficients are multiplied by $10^4$. Sample period: Jan. 2001 – Dec. 2004.

## Figure 2
## Cumulative impulse responses




Note: The figure shows the daily and weekly cumulative responses to a one standard deviation shock of the variables from a structural vector autoregressive model with $FIN, BANK, CORP$ and the log EURSEK exchange rate change $\Delta s$ as endogenous variables and with $didiff$ and $dislopediff$ as exogenous variables. The figure displays multiple graphs, with an impulse response to each shock in separate graphs. Cumulative response to Cholesky one standard deviation innovations +/- 2 s.e. Sample period: January 2001 – December 2004.

# *Chapter II*

# Herding the Scapegoats: Foreign Exchange Order Flow and the Time-Varying Effect of Fundamentals

Anna Lindahl[*], Michael Moore[†], Dagfinn Rime[‡], Ali Shehadeh[§]

**Abstract**

The poor performance of macroeconomic exchange rate models in and out-of-sample is well documented in the literature. One reason for this result is the impact of 'scapegoat' effects; participants attach different weights to different macro fundamentals in different periods. In contrast, microstructure approaches to exchange rate determination demonstrate the importance of order flow to both explain and forecast exchange rates. Using *monthly* data sets for order flow and macro 'fundamentals' for the five currency pairs ($/€, ¥/$, $/£, NOK/€ and SEK/€) we find evidence supporting scapegoat effects. In particular, (i) the instability in the returns-fundamentals relation is matched by a similar instability in the relation between order flow and fundamentals; and (ii) the predicted order flow from the time-varying relation with fundamentals (macro-induced order flow) has strong explanatory power for spot returns. We conclude that the consistent and more stable impact of order flow, in part, comes from the fact that it absorbs and acts as a sufficient statistic for scapegoat effects.

*Keywords:* Foreign exchange microstructure, Unstable fundamentals, Scapegoat theory.

*JEL classification:* F31, F41, G15.

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# 1 Introduction

In this paper we aim to merge two strands of the literature on foreign exchange (FX) rates. On the one hand, the study of the unstable relation between macroeconomic fundamentals and exchange rates, and on the other hand the microstructure approach to exchange rates and its focus on the importance of order flow.[1] Both of these approaches have emerged as answers to the question of what drives exchange rates, a question that has engaged economists for a long time. The fact that exchange rate models, based on traditional macro variables, are often outperformed by a random walk, first documented by Meese and Rogoff in 1983, still remains true. Macroeconomic fundamentals appear to be very weak predictors of exchange rate movements, described by Obstfeld and Rogoff (2001) as the "exchange rate disconnect puzzle." The low explanatory power of fundamentals for exchange rate movements stand in stark contrast to the high explanatory power of order flow. By merging these two approaches we contribute to the solution of two puzzles in exchange rate economics: First we show that macroeconomic fundamentals do explain exchange rate movements, contrary to the finding of the "disconnect" literature. Second, by showing that fundamental information gets impounded into exchange rates via order flow we provide an explanation for the high explanatory power of order flow.

A possible reason for the low explanatory power in the fundamental-based model is instability in the relationship between exchange rates and macroeconomic fundamentals. This is a well-known problem for anyone who has ever tried to build empirical models for exchange rates, and is formally documented by, for example, Sarno and Valente (2009). It is not so much that fundamentals are unimportant for exchange rates, but rather that the results are unstable so that it is difficult to rely on such models for e.g. investment or policy advice. The

[1]Order flow is defined as the net of buyer- and seller-initiated transactions (Lyons 2001). The initiator to a trade is the party paying the transaction costs, i.e., demanding liquidity. Since order flow measures the transaction of just one of the parties to a trade it will not necessarily equal zero in equilibrium, as opposed to net buying measured over both counterparties. Order flow takes positive values for net buying-pressure and negative for net selling-pressure.

fundamentals that seem to be important in one sample period become unimportant when the sample is extended. While this paper is on exchange rates, the unstable relationship could apply to other forward looking financial or macroeconomic variables. Stock and Watson (1996) first showed that the phenomenon of parameter instability in macroeconomic data is widespread.[2] Sarno and Valente (2009) find that "(exchange rate) models that optimally use the information in the fundamentals change often and this implies frequent shift in the parameters". Such instability has also been reported by Meese and Rogoff (1988).

In stark contrast, over the past two decades a new literature has emerged which points to a strong link between spot rate dynamics and order flows. This new microstructure literature provides evidence that order flows account for a large part of the variability in spot exchange rates for horizons ranging from a few minutes to macroeconomic relevant frequencies like months and quarters. Evans and Lyons (2002) show that inter-dealer order flow explains up to 60% of the daily variation in the dm/dollar and yen/dollar rates. Subsequent research has shown similar results and these findings appear remarkably robust, across different sets of exchange rates, frequencies, and sample periods. Such strong explanatory power suggests a relatively stable relation with exchange rates.

The puzzle, therefore, really is why fundamentals are so unstable predictors while order flow is such a stable predictor. In this paper, we try to answer this question by formally analyzing the notion that market participants over time change the "themes" that are the focus of the market. This is in accordance with the scapegoat theory of Bacchetta and van Wincoop (2004, 2013). Some information about the structural parameters can be derived by analyzing the macroeconomic data and exchange rates. But these data are also driven by shocks to *unobserved* fundamentals. Such unobserved fundamentals can generate considerable confusion in the short to medium run. When the exchange rate fluctuates due to an unobserved

[2] Subsequent contributions include Boivin (2006), Canova (2005), Clarida, Gali and Gertner (2000), Cogley and Sargent (2005).

macroeconomic shock, it can be optimal for agents to blame it on an observed macro fundamental by giving it more weight and therefore making it a "scapegoat". For example when the dollar depreciates and there is no clear consensus in the market for what causes the depreciation, it may be natural for traders in the foreign exchange market to attribute it to, for example, a large current account deficit even though the depreciation is actually unrelated to the current account deficit. Hence, the market searches for an explanation to the observed exchange rate change and may attribute it to some observed macro indicator. This macro indicator then becomes a scapegoat, which may influence the trading strategies of the market. Over time, different macro indicators will be taken as scapegoats so that the weights attributed to the indicators will change. The basic mechanism behind the scapegoat-effect is that there is confusion in the market about the true cause of the exchange rate fluctuations, creating space for market participants to have alternative explanations.

The crux of the paper is to take seriously that these scapegoat explanations influence trading strategies, and hence order flow. We conjecture that order flow has a stable impact on exchange rates because it reflects the current "theme" of the market. Market participants can learn about the new scapegoat by searching for macro data that fit an observed pattern in the exchange rate, and then make conjectures about the beliefs of the rest of the market, or simply learn about the new implications for FX by looking at order flow. Order flow becomes a single "factor" that aggregates the fundamentals that are currently in fashion by a majority of the market participants. However, the flip side of this is that instability between fundamentals and exchange rates is mirrored with a similar instability between fundamentals and order flow. By merging these two strands of literature we make two distinct contributions. First, we provide an explanation for what is driving order flow, and second, we provide an explanation for how macroeconomic fundamentals actually become impounded in exchange rates. Order flow has a stable relationship with returns. Macro variables have an impact on returns but it varies over time. Order flow acts as a form of sufficient statistic for macro variables, essentially accounting for this time variation in parameters. Our empirical results are based on long samples of order flow data at the macroeconomically relevant monthly frequency for five currency pairs: dollar/euro, yen/dollar, dollar/sterling, and the two cross rates Swedish krona and Norwegian kroner against euro. The three first being the three most traded currency pairs globally (BIS, 2013).

The paper is organized as follows. In section 2 we survey the evidence on the instability of the relation between exchange rates and macroeconomic fundamentals, and present the main features of Bacchetta and van Wincoop's (2004, 2013) scapegoat theory. We also discuss how changing "themes" of the market, in the manner of scapegoat stories, can be linked to order flow and our empirical tests of the relation. Section 3 presents the data used for the empirical analysis while in section 4 we present the empirical results. Section 5 concludes.

## 2 Background

### 2.1 The disconnect puzzle and the unstable FX-fundamentals relation

A great deal of research has investigated the relationship between exchange rates and macroeconomic fundamentals. The overall picture is that the relationship between exchange rates and fundamentals is either very weak or non-existent in the data at all. Hence, exchange rates and fundamentals are "disconnected". In a comprehensive investigation, Cheung et al. (2005) evaluate a wide range of empirical models and come to the conclusion that the results of Meese and Rogoff (1983) still hold true.

However, recent results by Sarno and Valente (2009) suggest that economic models were previously rejected not because the fundamentals are completely unrelated to exchange rate fluctuations, but because the relationship is unstable over time and thus difficult to capture.

Models perform poorly because of frequent shifts in the set of fundamentals driving foreign exchange. Many reasons for the unstable effect of macro fundamentals on exchange rates are discussed in the literature, including the instability in demand for money, changes in patterns of global trade and changes in policy regimes.

From reading the financial press, it also is clear that the participants in foreign exchange markets regularly change foot when it comes to explaining the underlying causes of exchange rate fluctuations. Practitioners often refer to these changes as the "themes" of the market. In a series of surveys, Cheung and Wong (2000), Cheung and Chinn (2001) and Cheung et al. (2004) have documented that traders change view over time on what constitutes an "important" macroeconomic variable.

More recent and systematic surveys confirm this feature. Fratzscher et al. (2014) use monthly survey data for a set of twelve currencies over almost 12 years and find large time variation in the importance that FX traders attach to different macro fundamentals as determinants of exchange rates. To the extent market participants affect exchange rates through their trading actions, this might lead to an unstable relationship between exchange rates and macro fundamentals. Furthermore Fratzscher et al. find that a model accounting for parameter instability is superior to a constant-parameter model.

Bacchetta and van Wincoop (2004, 2013) develop a scapegoat theory for the large and frequent variations in the relationship between the exchange rate and macro fundamentals. They consider the possibility that the exchange rate may change for reasons that have nothing to do with observed macro fundamentals, for example, due to unobserved liquidity trades. It may then be natural for the market participants to search for an explanation and attribute the change to some observed macro indicator, thereby making that particular macro variable a "scapegoat." The scapegoat-variable is then given excessive weight in explaining the exchange rate movements. Over time, different observed variables may become scapegoats, so that the weights attributed to macro variables change.

The basic mechanism behind the scapegoat story is that there is uncertainty about the structural parameters in the economy. With a forward looking variable like the exchange rate, the relationship is determined by the expectations of the structural parameters rather than the parameters themselves. These expectations can vary significantly over time and give rise to a highly unstable relationship between exchange rates and fundamentals. Investors do not know whether an exchange rate fluctuation is to be explained by unobserved fundamentals such as liquidity or hedging trades, or by an unusually large weight to certain observed macro fundamentals. It is then quite rational to blame some factor that one can actually observe, in particular a macro fundamental that is deviating significantly from its long-run equilibrium level. This prediction is confirmed in the empirical work by Fratzscher et al. (2014).

## 2.2 Order flow and scapegoats

The microstructure approach to exchange rate economics, developed by Lyons (1997) and Evans and Lyons (2002), describes how changes in exchange rates are determined by a combination of innovations in public and private information (see Evans, 2011, for an overview). Private information is revealed via order flow and Evans and Lyons show that adding order flow to a standard exchange rate model increases the fit dramatically. In their sample period, the macro variables alone produce an $R^2$ statistic of 1% or lower while the inclusion of order flow increases it to above 50% for some currencies.

Actual trades are neither necessary nor sufficient for price movements in traditional macro models. When there is a common interpretation of the reaction of the exchange rate from a macroeconomic innovation, the exchange rate will move instantaneously from one level to the new level without any trade necessarily taking place. In order for trading to take place one needs some disagreement between the market participants. That is, order flow may play a role when there is uncertainty, and disagreement, about the structural parameters in the economy, like in the case of scapegoats.

Subsequent literature have shown that the relation between FX returns and order flow is robust over different exchange rates, sample periods and lengths, and different frequencies from intradaily to monthly and quarterly (see, e.g., Berger et al., 2008; Chinn and Moore, 2011; Rime and Tranvåg, 2012)[3]. Importantly, it is suggested that order flow is related to macroeconomic fundamentals. Love and Payne (2008) and Evans and Lyons (2008) find that order flow plays a role in transmitting the implication of macroeconomics news (see also Dominguez and Panthaki, 2006; Chaboud et al., 2008). Berger, Chaboud and Hjalmarsson (2009) show that there are in fact large and persistent variations over time in the relationship between returns and order flow, and they study how these variations, along with variations in the order flow itself, are linked to the time-series behavior of volatility. Evans and Lyons and other authors have argued that the contemporaneous explanatory power of order flow for exchange rate movements derives in great part from the fact that information relevant to the price is transmitted to the market through order flow, a point previously demonstrated by Hasbrouck (1991) for the stock market. To the extent that order flow represents information, the empirical specification of Berger, Chaboud and Hjalmarsson allow them to decompose the factors affecting volatility into two time-varying components: the flow of information itself and the sensitivity of the market to that information. Evans (2010) show that while macro and FX are "disconnected" the macro-movements that are predicted by order flow have strong explanatory power. Evans and Lyons (2005) find that order flow contains predictive power and outperforms a random walk. Similarly, Rime et al. (2010) find that forecasts based on order flow models generate substantial economic gains to investors in a dynamic asset allocation setting.

[3] See Evans and Rime (2012) for a survey.

The current paper builds on these papers, and in particular Evans (2010). Instead of focusing on how order flow can predict macro fundamentals, we focus on how changes in the weights attached to macro variables can predict order flow. In Fratzscher et al. (2014), order flow is included as a variable that captures the unobservable liquidity shock in the theoretical scapegoat model. As such, it is treated as orthogonal to the macroeconomy and the scapegoat. Our paper take their documentation of scapegoats as given and ask how the market participants eventually can learn and converge on a new scapegoat. We postulate that the existence of a new scapegoat gives rise to a heterogeneity across market participants which results in trading amongst them. Agents know there is an unexplainable deviation of the exchange rate vis-à-vis the fundamental, and that this will trigger a search for a scapegoat. In the initial search-stage, there is uncertainty about which macro-variable that will be selected and given excessive weight. As market participants receive market recommendations, observe trading made by others, read reports etc., they will subsequently converge on a new scapegoat.[4]

The mechanism described here is very similar to the one observed following macroeconomic announcements: After a macroeconomic announcement there may be uncertainty as to what the implication will be for exchange rates, and investors may start trading on their beliefs. During this process, order flow has been shown to be an even stronger predictor of prices than during non-announcement periods (see Love and Payne, 2008; Evans and Lyons, 2008). As the "votes" of the market are counted and a new consensus (equilibrium) is reached, the "extra" impact of order flow dies away.

[4] The focus of the current paper is empirical rather than theoretical. We will therefore not attempt to build a theoretical model of this process of converging on a new scapegoat.

# 3 Data

The data employed are at a monthly frequency for the following five exchange rates: US dollar/euro ($/€, hereafter), Japanese yen/US dollar (¥/$, hereafter), US dollar/British pound ($/£ hereafter), Swedish krona/euro (SEK/€, hereafter), and Norwegian kroner/euro (NOK/€, hereafter). In addition, we use data on macro fundamentals and on order flows for the five currency pairs. The sample period for $/€ and ¥/$ is from January 1999 to December 2007 (108 months), and from January 1999 to November 2011 for the three other currency pairs ($/£, SEK/€ and NOK/€, 155 months). The data are all obtained from Datastream. Since we do not have the same amount of observations for all currency pairs we find it necessary to shorten the longer samples, i.e., for $/£, SEK/€ and NOK/€, in order to be able to compare the results for all the currency pairs correctly. For completeness reasons we use both the truncated data as well as the non-truncated data sets since we find that all accessible data is valuable and should be examined. After all, we study the time varying effect of fundamentals so longer time series is in this respect meaningful.

## 3.1 Macro fundamentals data

We use eight macroeconomic variables at a monthly frequency for Japan, the Euro zone, the United States, the United Kingdom, Sweden and Norway. Firstly, the short-term three month interest rates. We use the Treasury bill rate for the US, the euro interbank offered rate (Euribor) for the Euro zone, the Tokyo interbank rate (TIBOR) for Japan, the London Interbank Offered rate (LIBOR) and the treasury bill rates for Sweden and Norway. Secondly the yield curve slope, calculated as the difference between the ten year interest rates and three month interest rates. Third, equity market returns[5]: the S&P 1500 for the United States, the Euro STOXX for the Euro zone, the Nikkei 500 for Japan, the FTSE for the UK, the OMX 30

[5] The use of equity return differentials is motivated by the Hau and Rey (2006) model of uncovered equity returns parity.

for Sweden and the OSEBX for Norway. Fourth, the rate of inflation based on the consumer price index (CPI) for the US, the Euro zone, Japan, UK, Norway and Sweden: it is used to calculate inflation rates. Fifth, money[6] stocks in the economy of each area. Sixth, we use retail sales as our monthly measure of economic activity in each area. Seventh, trade balances of each area. And last, the price of oil measured by the price of Brent crude. For data available at a daily frequency, such as the short-term interest rate, long-term interest rate, equity market return and the oil price, end of month values rather than period averages are used.

### 3.2 Exchange rate data

Data on end-of-month spot exchange rates for \$/€, ¥/\$, \$/£, SEK/€ and NOK/€ are also obtained from Datastream. The base currency is € in the case of \$/€-rates, (e.g., USD per euro), \$ in the case of ¥/\$ (JPY per USD), and £ in the case of \$/£ (USD per GBP). The \$/€, ¥/\$ and \$/£ are the most heavily traded currency pairs in the foreign exchange market. In the September 2013 survey by the Bank for International Settlements, spot transactions represent 38% of the daily average of the foreign exchange market turnover. 43% of the daily average of the global foreign exchange market turnover is in \$/€, ¥/\$ and SEK/€ currency pairs, divided as, 24.1% in \$/€, 18.3% in ¥/\$ and 0.5% in SEK/€. \$/€ and ¥/\$ are the top two on the list of traded currency pairs while SEK/€ is a representative non-dollar cross-rate[7].

[6] We used the broadest measure available for each country: M3 for Sweden and the euro-zone, M2 for the US and L for Japan (See http://www.boj.or.jp/en/statistics/outline/exp/data/exms01.pdf).
[7] Both SEK/€ and SEK/\$ are actively traded and total turnover in the SEK/€ is \$28 billion per day and \$55 billion for the SEK/\$. However the bulk of SEK/\$ volume (\$40 billion per day) is in FX swaps. In the spot market, which we are considering here, the proportions are reversed: the euro pair has almost twice the turnover of the dollar pair; see Bank for international Settlements (2013).

### 3.3 Order flow data:

The foreign exchange market is a two-tier market where the key intermediaries are the FX dealing banks. These dealers trade with the end-users of the currency in the retail market and with other dealers in the interbank market. End-users only very rarely trade with each other. Dealers primarily trade with each other through electronic brokers.[8] They either supply or consume (trade at) liquidity by entering limit orders or market orders to electronic brokers, currently Reuters D3000 and Electronic Broking Services (EBS). These two platforms have split the market between them, and our order flow data come from the dominant platform for each currency pair. EBS is the main platform for \$/€ and ¥/\$, where it accounts for an estimated 90% of the \$/€ brokered inter-dealer business and virtually all of ¥/\$ trading (Chinn and Moore, 2011), while Reuters D3000 is the dominant platform for trading in the three other pairs.[9] 50%-70% of turnover in major currency pairs is settled through the EBS and Reuters electronic platforms (Rime et al. 2010). Positive (negative) order flow means buying (selling) pressure on the base currency in the currency pair. Order flow is measured in billions of base currency for \$/€ and ¥/\$, while in number of trades for the \$/£, SEK/€ and NOK/€ cases.

[Figure 1 about here.]

Figure 1 depicts the relationship between monthly spot returns and their respective order flows. Visually, it appears that the order flow and spot returns are closely related.

[Table 1 and 2 about here.]

[8] Dealers also have the option of trading directly through electronic communication networks such as Reuters 2000-1 or through voice brokers. However these are considerably less important than they used to be.

[9] The EBS data were made available to us at the minutely frequency with the trade sign observed electronically without error. The Reuters data were originally more granular: we have tick-by-tick observations on all trades and all limit orders (bid and ask tradeable quotes) timed to the thousand of a second. In order to create order flow we match the transaction price with the bid or the ask, being a buy market order (positive order flow) if it is traded at the ask and vice versa.

Table 1 and 2 present the descriptive statistics for spot returns and order flows. Some of their features are noteworthy. For $/€ and ¥/$, the mean of spot returns is not statistically different from zero. The mean of order flow is positive in four out of five cases, implying buying pressure on the base currency over the sample period on average.

# 4 Empirical analysis

Our empirical analysis basically builds on the following simple idea: Exchange rates and fundamentals are not disconnected, but since different macro-themes appear and disappear in the market, a model with constant parameters will give weak results. Order flow, on the other hand, is strongly related to exchange rates over both long and short samples, suggesting a more stable relation with exchange rates. However, why order flow has such strong explanatory power is not well understood.

We ask if order flow's strong relation is due to being a sufficient statistic for the direction of the macro fundamental in fashion at a particular moment. To this end, we investigate if the unstable relation between exchange rates and fundamentals is matched by a similar unstable relation between order flow and fundamentals. If so, this suggest an explanation for why order flow is such a strong predictor of exchange rates.

The analysis will proceed in four steps, developed further in the following sections: First, we confirm previous results that order flow has relatively strong (and fundamentals relatively weak) explanatory power for spot returns. Second, we show that the relation between fundamentals and exchange rates is unstable, and that the relation between order flow and exchanges rate is less unstable. Next, we analyze our key hypothesis, namely that the instability between fundamentals and exchange rates is matched with a similar pattern between fundamentals and order flow. Finally, we show that the order flow induced by the time-varying fundamentals actually partly explains exchange rate movements.

The analysis focus on the results from the estimations of the full sample but although values may differ somewhat the results generated by the truncated sample turn out to be qualitatively similar. Hence, when we discuss the results our conclusions relate to both the full and truncated samples unless otherwise mentioned.

### 4.1 Explanatory Power of Order Flow and Fundamentals

For the empirical analysis, we start with the following model:

$$\Delta S_t = \alpha + \gamma' X_t + \beta OF_t + \varepsilon_t, \tag{1}$$

where $\Delta S_t$ is the change in the log spot exchange rate (returns) between $t$ and $t-1$, $X_t$ is a vector of macro variables including the short-term interest rate differentials, the yield curve slope differential, the equity return differential, the inflation rate differential, money stocks (rate of growth), trade balances (first difference, in billions), retail sales (rate of growth), and the oil price (rate of growth). $OF_t$ is the monthly order flow. Differentials of macro-variables are defined as the value for the country of the quoting currency less the value for the country of the base currency (e.g. US-value minus EU-value for \$/€).

[Table 3 and 4 about here.]

Table 3 and 4, present three benchmark regressions over the whole sample as well as the restricted, or truncated, sample. These regressions consist of three different versions of the model specified above. The first one is spot returns regressed on the whole set of macro variables as specified above. This regression sets $\beta = 0$ and is denoted “M” henceforth. The second regression is a simple Kyle (1985) type of regression with foreign exchange return regressed on order flow alone (i.e. setting $\gamma = 0$) and we denote it as "OF". Our third regression takes all the macro variables as in the previous model but adds the order flow variable as regressor and is denoted "M-OF".

In the three cases, the exchange rate disconnect puzzle emerges clearly by looking at the in-sample goodness of fit measured by the $\bar{R}^2$ of the M specification. These results are consistent with most previous results. Our macro fundamentals account only for 10%, 13% and 8%, or even negative in the truncated sample, of the monthly changes of \$/€, ¥/\$ and SEK/€ exchange rates, respectively. For \$/€ and ¥/\$, the two interest rate variables are correctly signed - negative, in accordance with the price monetary model, but not with uncovered interest rate parity. The exact opposite is true for SEK/€ although both variables are insignificant in the \$/€ and SEK/€ cases.

There is a noticeable difference in the results of the OF specification. In the \$/€ and SEK/€ cases order flow as the lone independent variable results in an $\bar{R}^2$ of 13% and 14%, respectively, while it is as high as 32% in the ¥/\$ case. The sign of the coefficient on order flow is positive and therefore correctly signed. Buying pressure on the Euro results in an appreciation of the Euro against the US dollar and Swedish krona. Specifically, a one billion € increment in order flow results in an increase in the \$/€ and SEK/€ exchange rates by about 10 and 136 basis points respectively. In the case of ¥/\$, a one billion increase in US dollar order flow results in an increase in the ¥/\$ exchange rate by about 14 basis points, an appreciation in the US dollar against the Japanese yen. As the \$/€ and ¥/\$ markets are relatively more liquid than the SEK/€ market, the price impact of order flow on the SEK/€ exchange rate is much higher. A comparison between the M specification and OF specifications suggests that order flow as the lone regressor variable has a higher explanatory power than that of all macro variables together. This holds for all currency pairs except \$/£.

Order flow thus seems to have more relevant information for exchange rate determination. In contrast to the notion that order flow is a significant variable in explaining exchange rate variation only in high frequency data and that its effect is transitory, the high significance level of our monthly-aggregated order flow in the OF specification provides evidence that order flow has explanatory power also at lower frequencies and that its effect is persistent.

The addition of order flow to macro fundamentals (M-OF) increases the in-sample goodness of fit for all currency pairs. For \$/€, ¥/\$ and NOK/€, some significant macro fundamentals in the M specification become either insignificant or less significant in the M-OF specification, though not in the case of SEK/€ and \$/£. Comparing the $\bar{R}^2$ of the three specifications (M, OF and M-OF), both order flow and macro fundamentals seem to add separate explanatory power, especially in the \$/€ and SEK/€ cases. However, the effects of macro fundamentals and order flow do not appear orthogonal, as seen from the, sometimes substantial, weakening of the macro results once order flow is included. This is consistent with what we present in the literature section; part of the macro fundamentals effect is impounded in the exchange rate directly, while another part is transmitted via order flow. Order flow captures some, but not all, of the impact from macro fundamentals. This is in line with previous research on order flow and exchange rates, namely that the impact of order flow reflects both a risk compensation for "portfolio" shifts as well as the underlying macro information that the trading decision is based on.

[Table 5 and 6 about here.]

Table 5 and 6 presents the model in which order flow, as a dependent variable, is directly regressed on the same set of macroeconomic fundamentals as discussed above (labelled OF-DV later):

$$OF_t = \tilde{\alpha} + \tilde{\gamma}\,' X_t + \tilde{\varepsilon}_t \tag{2}$$

The same notation as previously is used, where $OF_t$ and $X_t$ define order flow and macro fundamentals, respectively. This model shows the direct effect of macro fundamentals on order flow determination. There is a big difference in the $\bar{R}^2$ measures amongst the five currency pairs cases. It is 7%, 28%, 4%, 11% and about zero for \$/€, ¥/\$, £/\$, NOK/€ and SEK/€ respectively. The numbers are similar for the truncated sample. Although the $\bar{R}^2$ measure is low for all currency pairs except for ¥/\$, the results do point to a role for macro fundamentals in order flow determination. We return to this in the following sections. However, it is important to note that similarly with the previous regressions on the exchange rate, macro is expected to have a time varying effect on order flow. The coefficient of the macro variables are varying regardless whether they are regressed on the exchange rate or on order flow. Traders will find various macro themes governing the market in different periods; hence the macro variables will have a time varying influence on order flow.

## 4.2 Relative Instability of Fundamental and Order Flow Regressions

Our interpretation of the scapegoat theory suggests that one might expect that the effect of order flow on spot returns be more stable relative to macro fundamental effects. To evaluate this, we implement the following procedure.

Rolling regressions with a window size of 36 observations[10] are estimated for each of the model specifications we have considered until now: M, OF, M-OF and OF-DV. This

[10] We choose 36 in order to balance the need for a sufficient number of observations for estimation with an approximation to the life of a scapegoat theme. In order to check if our results are

produces a series of slope coefficients and t-statistics for each independent variable in the respective model specification. Then, the coefficient of variation (the absolute value of the standard deviation divided by mean) is calculated for the resulting slope coefficients and t-statistics for each independent variable in the respective specification. The conjecture here is that independent variables with smaller coefficients of variation have a more stable impact on the dependent variable in the respective specification.

[Table 7, 8 and 9, 10 about here.]

The results of this exercise are presented in tables 7, 8 and 8, 9 (OF-DV model). It is clear that the coefficients of variation of slope coefficients (panel A) and t-statistics (panel B) for the order flow variable (in both OF and M-OF) are noticeably smaller than those of any macro fundamental variable (in both M and M-OF) for all five exchange rate pairs. For \$/€ and £/\$ the coefficients for the equity differential variable are marginally larger in the truncated sample. This suggests that order flow has a more stable impact on exchange rate determination relative to macro fundamentals. The last line in panel A reports the coefficients of variation of the $\bar{R}^2$ resulting from rolling regressions for each model specification. The smallest ones are those of OF and M-OF which indicates that, in terms of the goodness of fit measured by $\bar{R}^2$ the regression equation as a whole is more stable with the inclusion of the order flow variable. This reinforces the impression that the inclusion of order flow as a regressor has a stabilizing effect.

The coefficients of variation of slope coefficients and t-statistics for the macro fundamentals in the OF-DV model point to the time-varying impact of these variables, and

robust for a different sample and window size, we use a rolling window size of 24 months for the truncated sample.

the unstable relationship between them and order flow. This also helps us understand the low $\bar{R}^2$ figures in the OF-DV regressions in Table 5 and 6. The weakest of these regressions were for the SEK/€ and £/$ pair. Not surprisingly, the coefficients of variation for this case are the poorest for any exchange rate.

### 4.3 The time-varying impact of fundamentals

In order to study how order flow may reflect the time-varying effect of fundamentals we examine in detail last section's regressions for models M and OF-DV where the dependent variables are the monthly spot return and order flow respectively, regressed on the macro variables.

[Figures 2-11 and 12-21 about here.]

Figures 2-11 and 12-21 track the slope coefficients and t-statistics, respectively for each of the variables from these two rolling regressions. None of the fundamentals appears to be stable in the exchange rate regression or the order flow regression. By simply eye-balling the two figures it appears that the instability in the (M)-model is being reasonably matched by a similar instability in the (OF-DV)-model. The same relation and behavior also hold for the rolling t-statistics in the respective models.

[Table 11 and 12 about here.]

It turns out that this is confirmed by the correlation of slope and t-statistics, as shown in Table 11 and 12. As expected, they are almost all positive. In the case of $/€, six out of eleven correlation coefficients of the rolling slope coefficients are above one-half, and five correlation coefficients of the rolling t-statistics are also in excess of 0.5. For SEK/€, seven correlation coefficients of the rolling slope coefficients and four of the rolling t-statistics are above 0.5. For ¥/$ and NOK/€, we note the strongest correlations, where nine out of eleven correlation coefficients of the rolling slope coefficients and ten correlation coefficients of the rolling t-statistics are over 0.5. For the truncated sample the results are somewhat weaker with only one currency pair, ¥/$, having seven slope coefficient correlations above one-half, the rest are around five to six. These results indicate that macro fundamentals affect both exchange rate and order flow in the same direction and even to the same extent.

While each individual macro fundamental will act as scapegoat only for a limited time period and hence show an unstable relation with the foreign exchange rate (and order flow) over time, order flow will display a more stable impact on the exchange rate since it becomes a proxy for the entire set of fundamentals. In this way, order flow acts as a sluice gate through which the themes in the market will materialize, no matter which macro variable is dominating the market at the moment.

## 4.4 The price impact of macro-induced order flow

The analysis in Section 4.3 above suggests that order flow is related to changes in the importance of macroeconomic fundamentals for the exchange rate, or put differently, to changes in scapegoat explanations. Previous research has shown that order flow is itself a very strong predictor for exchange rate movements, but we still do not have a clear understanding of why. If the movements in order flow induced by the changing focus of the market also move exchange rates we may have gained a better understanding of the exchange rate and order flow relation.

From the rolling regressions of order flow on fundamentals in Section 4.3 we use the coefficients and multiply these with the macro variables to create a predicted order flow:

$$OF_t^{Macro} = \widehat{OF}_t = c_t + \gamma_t \cdot Macro_t \quad (3)$$

This captures the part of order flow that is a time-varying function of fundamentals, i.e., of the fundamentals and their time-varying coefficients. We label this macro-induced order flow. In other words, any shift in the relative importance of the different macro fundamentals and, any change in their slope coefficients will be captured by the macro-induced order flow. In addition, we compute order flow residuals, that is, the difference between the actual order flow and macro-induced order flow to capture the part of order flow that is unrelated to macro fundamentals, such as; hedging, risk and inventory management trades.

[Table 13 and 14 about here.]

Using these two concepts, Tables 13 and 14 report results for different model specifications for the five currency pairs. In OFM-1, spot returns $\Delta \log(S_t)$ are regressed on both the macro-induced order flow $OF_t^{Macro}$ and order flow residuals $OF_t - OF_t^{macro}$ i.e., order flow caused by other factors than macro fundamentals.

$$\Delta \log(S_t) = c + \lambda_1(OF_t - OF_t^{macro}) + \lambda_2 OF_t^{Macro} + \varepsilon_{1,t} \quad (4)$$

In this model specification, macro fundamentals affect the exchange rate indirectly through the macro-induced order flow. For comparison purposes, we also reproduce the M specification in tables 13 and 14 in which spot returns are regressed directly on the set of macro fundamentals, over the truncated[11] full sample periods from January 2002 to December 2007 for the $/€ and ¥/$ and from January 2002 to November 2011 for the $/£, SEK/€ and NOK/€. For the truncated sample the period is February 2001 to December 2007 for all currencies. The results confirm that order flow is better able to explain exchange rate variations than the set of macro variables because for all five currency pairs, except for $/£ in the full sample, OFM-1 has a larger $\bar{R}^2$ than those for the M specification in which spot returns are regressed on only macro variables. In addition, for the five pairs in both samples, the macro-induced order flow (labeled $OF^{\ MACRO}$) in OFM-1 is significant and correctly signed and positive as are the order flow residuals ($OF^{RESID}$). It is worth highlighting that in the ¥/$, SEK/€ and NOK/€ cases the price impact of the macro-induced order flow is larger than that of order flow residuals. For the truncated sample this result holds for $/€ and ¥/$.[12]

It is reasonable to raise the objection that macro-induced order flow may not only capture the varying, unstable effect of macro but also capture the purely stable effect that is not time varying of macro fundamentals. To address this, we do the following: the macro induced order flow is regressed on the set of macro fundamentals[13]:

$$OF_t^{Macro} = c_t + \gamma \cdot Macro_t + \varepsilon_t \tag{5}$$

The fitted values of this regression are considered the 'stable' part of the macro induced order flow representing the stable relation between macro fundamentals and order flow, while the residuals of the same regression are the 'unstable' part representing the time-varying relation between macro fundamentals and order flow:

[11] Recall that the first 36 (full sample) and 24 (truncated sample) observations are needed to produce the first of the rolling regressions.
[12] Because the procedure we employed could suffer from generated regressor bias, we have bootstrapped the standard errors in Tables 13 and 14.
[13] The macro-induced order flow comes from a sequence of rolling regressions. This is a single stationary regression over the truncated sample.

$$OF_t^{Stab.Macro} = \widehat{OF_t^{Macro}} = c + \gamma \cdot Macro_t \tag{6}$$

For specification OFM-2 in Tables 13 and 14, spot returns are regressed on the two parts - stable and unstable - of the macro-induced order flow rather than the macro induced order flow as a whole as well as the order flow residuals from the rolling regression:

$$\begin{aligned} \Delta \log(S_t) = c + \lambda_1(OF_t - OF_t^{macro}) + \lambda_{2,1} OF_t^{Stab.Macro} + \\ + \lambda_{2,2}(OF_t^{Macro} - OF_t^{Stab.Macro}) + \varepsilon_{2,t} \end{aligned} \tag{7}$$

For the full sample the three order flow variables are positive and significant in all currency pairs, except the \$/€ and \$/£ in the full sample. In the \$/€ case, OF-UNSTABLE is insignificant, which could be interpreted as the time-varying relation between macro fundamentals and the exchange rate does not strongly enough match the time-varying relation between macro fundamentals and order flow over our sample period. In the \$/£ case, OF-STABLE is insignificant which could be interpreted as the stable relation between macro fundamentals and the exchange rate is weak. In the truncated sample all three order flow variables are significant in all currency pairs.

We report the results of two further experiments with macro-induced order flow in Table 13 and 14. For the OFM-3 specification, spot returns are regressed on order flow residuals, the macro-induced order flow as a whole and the set of macro fundamentals:

$$\begin{aligned} \Delta \log(S_t) = c + \lambda_1(OF_t - OF_t^{macro}) + \lambda_2 OF_t^{Macro} + \\ + \beta \cdot Macro_t + \varepsilon_{3,t} \end{aligned} \tag{8}$$

In OFM-4, spot returns are regressed on only the order flow residuals and the set of macro fundamentals:

$$\Delta \log(S_t) = c + \lambda_1(OF_t - OF_t^{macro}) + \beta \cdot Macro_t + \varepsilon_{3,t} \tag{9}$$

For all five currency pairs, the larger $\bar{R}^2$ for OFM-3 compared to the OFM-1 specification confirms the notion that both order flow and macro fundamentals add to the explanatory power in explaining exchange rate determination.

For the ¥/$ pair, OFM-3 shows that the significant macro fundamentals in OFM-4 and M became either insignificant or less significant after the inclusion of the macro-induced order flow. In other words, macro fundamentals affect the exchange rate through the order flow channel and, in large part, the effects of macro fundamentals are transmitted to the exchange rate via the order flow channel. However, we still have macro fundamental effects which have not been captured by the macro induced order flow, because the $\bar{R}^2$ has increased from 40% in OFM-1 to 44% in OFM-3. In contrast, for both the $/€ and SEK/€ pairs, the OFM-3 results indicate that even after the inclusion of the macro induced order flow the significant macro fundamentals in OFM-4 and M remained significant. For the SEK/€ case, unlike for $/€, macro-induced order flow is significant in OFM-3. These results could be interpreted as that, over our sample period, there are more direct macro fundamental effects on the $/€ and SEK/€ exchange rates, so that the macro induced order flow did not capture these effects. (An example could be that a higher than expected production statistic makes the foreign exchange market agree about a new level which causes a shift in demand for the currency whereby no order flows are traded.) However, the macro induced order flow still adds to the explanatory power in exchange rate determination where the inclusion of the macro induced order flow resulted in an increase in the $\overline{R}^2$ from 28% in the OFM-4 to 30% in the OFM-3 and from 26% to 34% for the \$/€ and SEK/€ cases respectively.

In this sub-section, we have shown the significant role of macro induced order flow in exchange rate determination and how macro fundamentals make their impact through the order flow channel. Moreover, as long as order flow is able to capture the scapegoat effects that govern the market, it will exhibit a more stable impact on the exchange rate relative to macro fundamentals. Whatever the views of market participants on macro fundamentals, and whatever the scapegoat at any moment of time is, order flow will absorb these changing factors and work like an "adaptor" in determining the exchange rate.

# 5 Conclusion

A possible explanation for the low explanatory power in fundamentals-based exchange rate models is the instability of the coefficients in the relationship between exchange rates and macroeconomic fundamentals. This has been formally documented by, e.g., Sarno and Valente (2009). The problem appears because some fundamentals seem to have an impact on the currency in some periods but not in others.

Instead it has been found in previous literature that order flow has a strong and stable relation with the exchange rate. So the question is why order flow works but economic fundamentals seem to fail? There is ample anecdotal evidence that market participants blame individual fundamentals or "themes" for exchange rate movements, with such blame often shifting rapidly across different fundamentals over time. This is in accordance with the Bacchetta and van Wincoop (2004, 2013) scapegoat story: some variable is given an excessive weight during some period. If the exchange rate is driven by unobservable factors or it is unclear how to interpret the actual effect of observable fundamentals, then it is perfectly understandable, though not rational, for the market to search for a "scapegoat" indicator they can actually observe. We argue that these scapegoat explanations influence trading strategies and hence order flow and that the stable impact of order flow on the exchange rate exists because order flow incorporates the current ”theme” of the market.

The present paper constitutes an attempt at linking the scapegoat theory by Bacchetta and van Wincoop and the order flow theory of exchange rates. We do so by using long runs of *monthly* inter-dealer order flow on five currency pairs, \$/€, ¥/\$, \$/£, NOK/€ and SEK/€ along with data on traditional macroeconomic determinants. First of all we establish the fact that order flow exhibits a strong impact on the exchange rate compared to monetary variables even at the macroeconomically relevant monthly frequency. Furthermore, we show that the macro parameters are unstable in their impact on the five currency pairs whereas the relation between the exchange rates and order flow appears more stable. Our results from the rolling regressions also show that the impact of macro factors behave similarly on both the exchange rate and on order flow, which supports our hypothesis that macro fundamentals are the underlying cause for order flow.

When we predict order flow from macro fundamentals – macro-induced order flow - and use it in regressions on the exchange rates, we find that both the macro-induced and the residual order flows have a positive and significant impact on all five spot returns in both samples and that the impact of macro predicted order flow is larger for three out of the five pairs in the full sample - ¥/\$, SEK/€ and NOK/€ and for two in the truncated sample - \$/€ and ¥/\$. In addition, when we control for the part of time varying order flow that is stable across the full sample we get an unstable part interpreted as the time-varying impact of fundamentals on order flow which has a positive and significant impact on the exchange rate for all currency pairs except for \$/€ in the full sample.

Taken together, our results are highly suggestive of the view that order flow is the channel through which time-varying macro fundamentals work to move the exchange rate.

This evidence supports our hypothesis that order flow in essence is macroeconomic fundamentals in disguise, i.e., it is the vehicle through which the different opinions of the underlying reasons for changes in the foreign exchange rate get materialized.

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Table 1: Descriptive Statistics, full sample

Notes: "Spot" is monthly change in log of the spot exchange rates, measured in percentage points. Exchange rates are presented as quoting currency over base currency, so e.g. $/€ means US dollars pr euro. According to foreign exchange convention £ is the base currency against $ but in this paper we denote it as the quoting currency."OF" is monthly-aggregated order flow, measured in millions of base currency for $/€ and ¥/$ and in number of trades for the rest. All exchange rates are taken end-of-month from Datastream, starting in January 1999. Table 1 show descriptive statistics for samples ending in December 2007 (nine years) for $/€ and ¥/$ and in November 2011 for the rest (almost 13 years). Table 2 shows the statistics for all currency pairs with the shorter sample size of $/€ and ¥/$. Order flow is from EBS for $/€ and ¥/$ and Reuters for the rest. "AC(1)" is first-order autocorrelation.

| | | Mean | Median | St.Dev. | Skew. | Kurt. | Min. | Max. | AC(1) | Obs. |
|---|---|---|---|---|---|---|---|---|---|---|
| $/€ | Spot | 0.203 | -0.051 | 2.568 | 0.33 | 2.86 | -4.883 | 7.564 | 0.18 | 108 |
| | OF | 9592 | 9757 | 9338 | -0.27 | 3.07 | -15527 | 32364 | 0.38 | 108 |
| ¥/$ | Spot | -0.009 | 0.143 | 2.601 | 0.01 | 2.96 | -6.866 | 6.618 | 0.04 | 108 |
| | OF | 11699 | 13023 | 10285 | -1.22 | 6.93 | -34166 | 32780 | 0.27 | 108 |
| £/$ | Spot | 0.036 | -0.013 | 2.567 | 0.38 | 4.58 | -8.456 | 9.819 | 0.09 | 155 |
| | OF | -1178 | -1314 | 1837 | 0.23 | 3.48 | -6466 | 3932 | 0.25 | 155 |
| SEK/€ | Spot | -0.026 | -0.057 | 1.755 | 0.03 | 5.83 | -6.582 | 6.403 | -0.09 | 155 |
| | OF | 338 | 333 | 485 | -0.20 | 2.90 | -1077 | 1389 | 0.16 | 155 |
| NOK/€ | Spot | -0.091 | -0.159 | 2.016 | 0.16 | 7.55 | -9.435 | 9.048 | -0.09 | 155 |
| | OF | 105 | 177 | 506 | 0.16 | 5.03 | -1449 | 2245 | 0.12 | 155 |

Table 2: Descriptive Statistics, truncated sample

| | | Mean | Median | St.Dev. | Skew. | Kurt. | Min. | Max. | AC(1) | Obs. |
|---|---|---|---|---|---|---|---|---|---|---|
| $/€ | Spot | 0.203 | -0.051 | 2.568 | 0.33 | 2.86 | -4.883 | 7.564 | 0.18 | 108 |
| | OF | 9592 | 9757 | 9338 | -0.27 | 3.07 | -15527 | 32364 | 0.38 | 108 |
| ¥/$ | Spot | -0.009 | 0.143 | 2.601 | 0.01 | 2.96 | -6.866 | 6.618 | 0.04 | 108 |
| | OF | 11699 | 13023 | 10285 | -1.22 | 6.93 | -34166 | 32780 | 0.27 | 108 |
| £/$ | Spot | -0.166 | -0.101 | 2.125 | -0.10 | 2.602 | -5.236 | 4.681 | -0.07 | 108 |
| | OF | -1636 | -1531 | 1448 | -0.01 | 4.14 | -6011 | 2332 | 0.15 | 108 |
| SEK/€ | Spot | -0.004 | -0.032 | 1.440 | -0.59 | 5.88 | -6.582 | 3.227 | -0.07 | 108 |
| | OF | 352 | 311 | 481 | -0.18 | 3.12 | -1077 | 1389 | 0.16 | 108 |
| NOK/€ | Spot | -0.111 | -0.150 | 1.685 | 0.39 | 3.70 | -4.476 | 5.171 | 0.05 | 108 |
| | OF | 86 | 180 | 463 | -0.34 | 3.63 | -1157 | 1591 | 0.18 | 108 |

Table 3: Benchmark regressions over full sample

Notes: OLS estimates. Dependent variable is monthly spot return, i.e. first log difference (models M, OF, and M-OF in text). Subscript $b$ indicate a variable of the base currency (e.g. euro in $/€), while subscript $q$ indicate a variable of the quote currency (e.g. dollar in $/€). Superscript $diff$ indicate the difference between the figure of the quoting currency and that of the base currency, while "Δ" denotes first-difference of the variable. The regressors are defined as follows: $\Delta$IntRate$^{diff}$ is first difference of short-term interest rate differential; $\Delta$Slope$^{diff}$ is first difference of yield curve slope differential; $\Delta$Equity$^{diff}$ is equity return differential; Inflation$^{diff}$ is inflation rate differential; $\Delta M$ is growth of money stock; ΔRetail is growth of retail sales; ΔTradeBal is first difference of trade balance in billions of home currency; ΔOil is growth rate of oil price; and OF is monthly order flow (positive for buying pressure of base currency), and is measured in billions of base currency for $/€ and ¥/$ and in 1000 trades for the others. See Appendix for exact definition and sources of variables. Sample starts in January 1999 for all currency pairs, and ends in December 2007 for $/€ and ¥/$ and in November 2011 for the others.

| | $/€ | | | ¥/$ | | | $/£ | | | SEK/€ | | | NOK/€ | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | M | OF | M-OF | M | OF | M-OF | M | OF | M-OF | M | OF | M-OF | M | OF | M-OF |
| Constant | 0.607 | **-0.770** | -0.566 | -0.324 | **-1.697** | **-1.636** | -0.273 | **0.689** | 0.183 | -0.067 | **-0.488** | **-0.600** | -0.009 | **-0.326** | -0.219 |
| | (1.25) | (-2.32) | (-0.97) | (-0.72) | (-5.41) | (-3.47) | (-0.95) | (3.05) | (0.67) | (-0.33) | (-3.05) | (-2.90) | (-0.04) | (-2.37) | (-1.08) |
| $\Delta$IntRate$^{diff}$ | -1.689 | | -1.529 | **-3.912** | | -0.662 | **-3.047** | | **-1.880** | 0.031 | | -0.024 | **-4.181** | | **-2.817** |
| | (-1.09) | | (-1.04) | (-3.13) | | (-0.52) | (-2.65) | | (-1.76) | (0.03) | | (-0.02) | (-3.71) | | (-2.78) |
| $\Delta$Slope$^{diff}$ | -1.935 | | -1.760 | **-3.013** | | **-1.619** | **-3.005** | | **-2.038** | 1.082 | | 0.599 | -0.891 | | -0.206 |
| | (-1.37) | | (-1.31) | (-3.29) | | (-1.90) | (-2.87) | | (-2.11) | (1.13) | | (0.69) | (-0.97) | | (-0.25) |
| $\Delta$Equity$^{diff}$ | **0.281** | | **0.234** | **0.096** | | 0.002 | **0.379** | | **0.397** | 0.055 | | 0.031 | 0.031 | | 0.020 |
| | (3.14) | | (2.71) | (1.87) | | (0.04) | (4.50) | | (5.18) | (1.22) | | (0.74) | (1.11) | | (0.80) |
| Inflation$^{diff}$ | 1.301 | | 0.978 | 0.127 | | 0.159 | 0.417 | | -0.004 | -0.368 | | -0.307 | 0.003 | | -0.110 |
| | (0.92) | | (0.73) | (0.12) | | (0.17) | (0.90) | | (-0.01) | (-1.07) | | (-0.98) | (0.01) | | (-0.31) |
| $\Delta$M$_q$ | -0.605 | | -0.728 | 0.283 | | 0.323 | 0.288 | | **0.383** | **0.137** | | **0.151** | -0.187 | | -0.083 |
| | (-0.95) | | (-1.19) | (0.63) | | (0.81) | (1.32) | | (1.92) | (1.92) | | (2.32) | (-1.12) | | (-0.56) |
| $\Delta$Retail$_q$ | 0.176 | | 0.152 | -0.155 | | -0.037 | 0.110 | | 0.131 | 0.050 | | -0.013 | 0.004 | | 0.038 |
| | (0.75) | | (0.69) | (-0.71) | | (-0.19) | (0.57) | | (0.74) | (0.39) | | (-0.11) | (0.03) | | (0.33) |
| $\Delta$TradeBal$_q$ | -0.049 | | -0.033 | 0.000 | | 0.000 | -0.010 | | -0.010 | 0.065 | | -0.029 | **-0.054** | | -0.023 |
| | (-0.42) | | (-0.30) | (0.10) | | (0.10) | (-0.04) | | (-0.04) | (0.20) | | (-0.10) | (-1.87) | | (-0.88) |
| $\Delta$M$_b$ | -0.488 | | 0.214 | **1.384** | | 0.495 | **0.672** | | **0.883** | 0.054 | | 0.230 | 0.202 | | 0.080 |
| | (-0.80) | | (0.34) | (2.17) | | (0.84) | (1.68) | | (2.41) | (0.19) | | (0.87) | (0.66) | | (0.30) |
| $\Delta$Retail$_b$ | -0.048 | | -0.210 | -0.036 | | -0.089 | -0.186 | | -0.221 | -0.220 | | -0.277 | -0.006 | | -0.096 |
| | (-0.11) | | (-0.52) | (-0.15) | | (-0.43) | (-1.06) | | (-1.38) | (-0.92) | | (-1.27) | (-0.03) | | (-0.48) |
| $\Delta$TradeBal$_b$ | -0.045 | | -0.052 | 0.052 | | 0.033 | -0.027 | | -0.010 | 0.045 | | 0.041 | 0.104 | | **0.125** |
| | (-0.31) | | (-0.38) | (0.48) | | (0.34) | (-0.42) | | (-0.18) | (0.70) | | (0.69) | (1.55) | | (2.13) |
| $\Delta$Oil | -0.006 | | -0.016 | **-0.047** | | **-0.035** | **-0.046** | | **-0.034** | **-0.038** | | **-0.039** | **-0.071** | | **-0.047** |
| | (-0.27) | | (-0.72) | (-1.97) | | (-1.66) | (-2.61) | | (-2.10) | (-3.18) | | (-3.61) | (-5.01) | | (-3.60) |
| OF | | **0.101** | **0.087** | | **0.144** | **0.133** | | **0.554** | **0.523** | | **1.365** | **1.397** | | **2.236** | **1.686** |
| | | (4.09) | (3.33) | | (7.15) | (5.27) | | (5.34) | (5.56) | | (5.04) | (5.56) | | (8.39) | (6.47) |
| adj.$R^2$ | 0.10 | 0.13 | 0.18 | 0.13 | 0.32 | 0.32 | 0.25 | 0.15 | 0.38 | 0.08 | 0.14 | 0.24 | 0.28 | 0.31 | 0.44 |

Table 4: Benchmark regressions over truncated sample

Notes: OLS estimates. Dependent variable is monthly spot return, i.e. first log difference (models M, OF, and M-OF in text). Subscript $b$ indicate a variable of the base currency (e.g. euro in \$/€), while subscript $q$ indicate a variable of the quote currency (e.g. dollar in \$/€). Superscript $diff$ indicate the difference between the figure of the quoting currency and that of the base currency, while "Δ" denotes first-difference of the variable. The regressors are defined as follows: $\Delta\text{IntRate}^{diff}$ is first difference of short-term interest rate differential; $\Delta\text{Slope}^{diff}$ is first difference of yield curve slope differential; $\Delta\text{Equity}^{diff}$ is equity return differential; $\text{Inflation}^{diff}$ is inflation rate differential; $\Delta M$ is growth of money stock; ΔRetail is growth of retail sales; ΔTradeBal is first difference of trade balance in billions of home currency; ΔOil is growth rate of oil price; and OF is monthly order flow (positive for buying pressure of base currency), and is measured in billions of base currency for \$/€ and ¥/\$ and in 1000 trades for the others. See Appendix for exact definition and sources of variables. Sample starts in January 1999 and ends in December 2007 for for all currency pairs.

| | \$/€ | | | ¥/\$ | | | £/\$ | | | SEK/€ | | | NOK/€ | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | M | OF | M-OF | M | OF | M-OF | M | OF | M-OF | M | OF | M-OF | M | OF | M-OF |
| Constant | 0.607 | **-0.770** | -0.566 | -0.324 | **-1.697** | **-1.636** | -0.477 | **0.903** | 0.495 | 0.019 | **-0.442** | **-0.474** | -0.103 | **-0.297** | -0.346 |
| | (1.25) | (-2.32) | (-0.97) | (-0.72) | (-5.41) | (-3.47) | (-1.22) | (3.24) | (0.32) | (0.07) | (-2.81) | (-2.01) | (-0.33) | (-2.22) | (1.28) |
| $\Delta\text{IntRate}^{diff}$ | -1.689 | | -1.529 | **-3.912** | | -0.662 | **-3.165** | | **-2.554** | 0.204 | | 0.552 | **-5.005** | | **-2.771** |
| | (-1.09) | | (-1.04) | (-3.13) | | (-0.52) | (-2.68) | | (-2.40) | (0.17) | | (0.51) | (-3.93) | | (-2.39) |
| $\Delta\text{Slope}^{diff}$ | -1.935 | | -1.760 | **-3.013** | | **-1.619** | **-3.796** | | **0.986** | 0.516 | | 0.583 | -2.864 | | -1.857 |
| | (-1.37) | | (-1.31) | (-3.29) | | (-1.90) | (-3.49) | | (-3.04) | (0.52) | | (0.67) | (-2.57) | | (-1.91) |
| $\Delta\text{Equity}^{diff}$ | **0.281** | | **0.234** | **0.096** | | 0.002 | **0.340** | | **0.336** | -0.050 | | -0.074 | 0.021 | | 0.019 |
| | (3.14) | | (2.71) | (1.87) | | (0.04) | (3.75) | | (4.15) | (-0.94) | | (-1.61) | (0.64) | | (0.70) |
| $\text{Inflation}^{diff}$ | 1.301 | | 0.978 | 0.127 | | 0.159 | -0.312 | | -0.474 | -0.164 | | -0.024 | 0.359 | | 0.172 |
| | (0.92) | | (0.73) | (0.12) | | (0.17) | (-0.62) | | (-1.04) | (-0.45) | | (-0.07) | (0.83) | | (0.46) |
| $\Delta\text{M}_q$ | -0.605 | | -0.728 | 0.283 | | 0.323 | 0.437 | | 0.316 | 0.069 | | **0.096** | -0.112 | | -0.026 |
| | (-0.95) | | (-1.19) | (0.63) | | (0.81) | (1.15) | | (0.93) | (1.04) | | (1.65) | (-0.64) | | (-0.17) |
| $\Delta\text{Retail}_q$ | 0.176 | | 0.152 | -0.155 | | -0.037 | 0.109 | | 0.047 | **0.213** | | 0.124 | 0.201 | | 0.219 |
| | (0.75) | | (0.69) | (-0.71) | | (-0.19) | (0.44) | | (0.21) | (1.69) | | (1.11) | (1.50) | | (1.91) |
| $\Delta\text{TradeBal}_q$ | -0.049 | | -0.033 | 0.000 | | 0.000 | 0.318 | | 0.198 | 0.417 | | 0.207 | -0.008 | | 0.017 |
| | (-0.42) | | (-0.30) | (0.10) | | (0.10) | (1.03) | | (0.71) | (1.06) | | (0.60) | (-0.22) | | (0.52) |
| $\Delta\text{M}_b$ | -0.488 | | 0.214 | **1.384** | | 0.495 | **0.215** | | 0.359 | -0.051 | | 0.062 | 0.106 | | 0.128 |
| | (-0.80) | | (0.34) | (2.17) | | (0.84) | (0.44) | | (0.81) | (-0.15) | | (0.21) | (0.28) | | (0.40) |
| $\Delta\text{Retail}_b$ | -0.048 | | -0.210 | -0.036 | | -0.089 | -0.113 | | -0.123 | -0.119 | | -0.130 | -0.026 | | -0.064 |
| | (-0.11) | | (-0.52) | (-0.15) | | (-0.43) | (-0.65) | | (-0.79) | (-0.49) | | (-0.61) | (-0.10) | | (-0.29) |
| $\Delta\text{TradeBal}_b$ | -0.045 | | -0.052 | 0.052 | | 0.033 | 0.139 | | 0.103 | -0.013 | | -0.032 | 0.063 | | 0.030 |
| | (-0.31) | | (-0.38) | (0.48) | | (0.34) | (1.63) | | (1.34) | (-0.17) | | (-0.49) | (0.73) | | (0.40) |
| ΔOil | -0.006 | | -0.016 | **-0.047** | | **-0.035** | **0.003** | | **0.013** | **-0.023** | | **-0.025** | **-0.046** | | **-0.029** |
| | (-0.27) | | (-0.72) | (-1.97) | | (-1.66) | (0.15) | | (0.83) | (-1.88) | | (-2.39) | (-2.76) | | (-2.00) |
| OF | | **0.101** | **0.087** | | **0.144** | **0.133** | | **0.653** | **0.597** | | **1.244** | **1.308** | | **2.161** | **1.782** |
| | | (4.09) | (3.33) | | (7.15) | (5.27) | | (5.12) | (4.96) | | (4.70) | (5.44) | | (7.61) | (5.91) |
| adj.$R^2$ | 0.10 | 0.13 | 0.18 | 0.13 | 0.32 | 0.32 | 0.26 | 0.20 | 0.34 | -0.02 | 0.16 | 0.22 | 0.16 | 0.31 | 0.38 |

Table 5: Order flow regressed on macro, full sample

Notes: OLS estimates. Dependent variable is monthly order flow, positive for buying pressure of base currency (model OF-DV in text). Subscript $b$ indicate a variable of the base currency (e.g. euro in \$/€), while subscript $q$ indicate a variable of the quote currency (e.g. dollar in \$/€). Superscript $diff$ indicate the difference between the figure of the quoting currency and that of the base currency. The regressors are defined as follows: $\Delta$IntRate$^{diff}$ is first difference of short-term interest rate differential; $\Delta$Slope$^{diff}$ is first difference of yield curve slope differential; $\Delta$Equity$^{diff}$ is equity return differential; Inflation$^{diff}$ is inflation rate differential; $\Delta M$ is growth of money stock; $\Delta$Retail is growth of retail sales; $\Delta$TradeBal is first difference of trade balance in billions of home currency; and $\Delta$Oil is growth rate of oil price. See Appendix for exact definition and sources of variables. Sample start in January 1999 for all currency pairs, and end in December 2007 for \$/€ and ¥/\$ and in November 2011 for the others.

| | \$/€ | ¥/\$ | £/\$ | SEK/€ | NOK/€ |
|---|---|---|---|---|---|
| Constant | **13.404** | **9.889** | **-0.872** | **0.381** | **0.124** |
| | (7.45) | (6.08) | (-3.73) | (6.21) | (1.92) |
| $\Delta$IntRate$^{diff}$ | -1.828 | **-24.497** | **-2.229** | 0.039 | **-0.809** |
| | (-0.32) | (-5.45) | (-2.40) | (0.11) | (-2.53) |
| $\Delta$Slope$^{diff}$ | -1.997 | **-10.510** | **-1.849** | 0.345 | -0.406 |
| | (-0.38) | (-3.19) | (-2.18) | (1.19) | (-1.55) |
| $\Delta$Equity$^{diff}$ | 0.538 | **0.711** | -0.034 | 0.018 | 0.007 |
| | (1.62) | (3.86) | (-0.49) | (1.27) | (0.85) |
| Inflation$^{diff}$ | 3.692 | -0.241 | **0.804** | -0.044 | 0.067 |
| | (0.71) | (-0.06) | (2.14) | (-0.42) | (0.58) |
| $\Delta$M$_q$ | 1.404 | -0.301 | -0.182 | -0.010 | -0.062 |
| | (0.59) | (-0.19) | (-1.03) | (-0.46) | (-1.30) |
| $\Delta$Retail$_q$ | 0.264 | -0.890 | -0.039 | 0.045 | -0.020 |
| | (0.30) | (-1.14) | (-0.24) | (1.16) | (-0.54) |
| $\Delta$TradeBal$_q$ | -0.182 | 0.000 | 0.000 | 0.068 | **-0.019** |
| | (-0.42) | (0.02) | (-0.002) | (0.67) | (-2.27) |
| $\Delta$M$_b$ | **-8.022** | **6.699** | -0.405 | -0.126 | 0.072 |
| | (-3.53) | (2.92) | (-1.25) | (-1.44) | (0.83) |
| $\Delta$Retail$_b$ | 1.859 | 0.400 | 0.065 | 0.041 | 0.053 |
| | (1.19) | (0.48) | (0.46) | (0.56) | (0.83) |
| $\Delta$TradeBal$_b$ | 0.072 | 0.144 | -0.032 | 0.003 | -0.013 |
| | (0.14) | (0.36) | (-0.60) | (0.15) | (-0.68) |
| $\Delta$Oil | 0.109 | -0.090 | -0.023 | 0.001 | **-0.014** |
| | (1.28) | (-1.05) | (-1.63) | (0.24) | (-3.55) |
| adj.$R^2$ | 0.07 | 0.28 | 0.04 | -0.01 | 0.11 |

Table 6: Order flow regressed on macro, truncated sample

Notes: OLS estimates. Dependent variable is monthly order flow, positive for buying pressure of base currency (model OF-DV in text). Subscript $b$ indicate a variable of the base currency (e.g. euro in \$/€), while subscript $q$ indicate a variable of the quote currency (e.g. dollar in \$/€). Superscript $diff$ indicate the difference between the figure of the quoting currency and that of the base currency. The regressors are defined as follows: $\Delta$IntRate$^{diff}$ is first difference of short-term interest rate differential; $\Delta$Slope$^{diff}$ is first difference of yield curve slope differential; $\Delta$Equity$^{diff}$ is equity return differential; Inflation$^{diff}$ is inflation rate differential; $\Delta M$ is growth of money stock; $\Delta$Retail is growth of retail sales; $\Delta$TradeBal is first difference of trade balance in billions of home currency; and $\Delta$Oil is growth rate of oil price. See Appendix for exact definition and sources of variables. Sample starts in January 1999 and ends in December 2007 for all currency pairs.

| | \$/€ | ¥/\$ | £/\$ | SEK/€ | NOK/€ |
|---|---|---|---|---|---|
| Constant | **13.404** | **9.889** | **-1.629** | **0.377** | 0.136 |
| | (7.45) | (6.08) | (-5.46) | (4.05) | (1.50) |
| $\Delta$IntRate$^{diff}$ | -1.828 | **-24.497** | **-1.025** | -0.266 | **-1.253** |
| | (-0.32) | (-5.45) | (-1.14) | (-0.58) | (-3.37) |
| $\Delta$Slope$^{diff}$ | -1.997 | **-10.510** | **-1.339** | -0.052 | **-0.565** |
| | (-0.38) | (-3.19) | (-1.62) | (-0.14) | (-1.73) |
| $\Delta$Equity$^{diff}$ | 0.538 | **0.711** | 0.005 | 0.019 | 0.001 |
| | (1.62) | (3.86) | (0.07) | (0.97) | (0.07) |
| Inflation$^{diff}$ | 3.692 | -0.241 | **0.271** | -0.107 | 0.105 |
| | (0.71) | (-0.06) | (0.70) | (-0.78) | (0.83) |
| $\Delta$M$_q$ | 1.404 | -0.301 | 0.203 | -0.021 | -0.048 |
| | (0.59) | (-0.19) | (0.70) | (-0.85) | (-0.95) |
| $\Delta$Retail$_q$ | 0.264 | -0.890 | 0.104 | 0.068 | -0.010 |
| | (0.30) | (-1.14) | (0.55) | (1.44) | (-0.26) |
| $\Delta$TradeBal$_q$ | -0.182 | 0.000 | 0.202 | 0.161 | -0.014 |
| | (-0.42) | (0.02) | (0.86) | (1.10) | (-1.29) |
| $\Delta$M$_b$ | **-8.022** | **6.699** | -0.241 | -0.087 | -0.012 |
| | (-3.53) | (2.92) | (-0.64) | (-0.69) | (-0.11) |
| $\Delta$Retail$_b$ | 1.859 | 0.400 | 0.016 | 0.008 | 0.022 |
| | (1.19) | (0.48) | (0.12) | (0.09) | (0.29) |
| $\Delta$TradeBal$_b$ | 0.072 | 0.144 | 0.061 | 0.015 | 0.019 |
| | (0.14) | (0.36) | (0.93) | (0.53) | (0.74) |
| $\Delta$Oil | 0.109 | -0.090 | -0.018 | 0.002 | **-0.009** |
| | (1.28) | (-1.05) | (-1.32) | (0.46) | (1.94) |
| adj.R2 | 0.07 | 0.28 | -0.03 | -0.02 | 0.11 |

Table 7: Coefficients of variation of rolling slope coefficients and rolling t-statistics: Spot-return regressions, full sample

Notes: Table reports coefficients of variation (absolute value of standard deviation divided by mean) of rolling slope coefficients (panel A) and t-statistics (panel B) for each variable resulting from rolling regressions of different model specifications. The last line of panel A, labelled "adj.$R^2$, reports the coefficients of variation of the sequence of adjusted $R^2$ from the rolling regressions. See notes to Table 2 for variable definitions and regression specifications. Sample start in January 1999 for all currency pairs, and end in December 2007 for \$/€ and ¥/\$ and in November 2011 for the others.

| | \$/€ | | | ¥/\$ | | | \$/£ | | | SEK/€ | | | NOK/€ | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | M | OF | M-OF | M | OF | M-OF | M | OF | M-OF | M | OF | M-OF | M | OF | M-OF |
| A: Slope Coefficients | | | | | | | | | | | | | | | |
| $\Delta$IntRate$^{diff}$ | 25.15 | | 1.47 | 0.51 | | 1.28 | 1.15 | | 3.96 | 7.44 | | 4.54 | 0.94 | | 1.43 |
| $\Delta$Slope$^{diff}$ | 1.61 | | 4.71 | 0.45 | | 0.60 | 0.67 | | 1.45 | 4.39 | | 6.22 | 3.12 | | 245.74 |
| $\Delta$Equity$^{diff}$ | 0.63 | | 0.51 | 0.68 | | 5.64 | 0.52 | | 0.44 | 4.96 | | 3.29 | 8.13 | | 46.95 |
| Inflation$^{diff}$ | 0.56 | | 1.63 | 1.37 | | 8.95 | 2.01 | | 1.63 | 1.98 | | 3.83 | 8.56 | | 28.38 |
| $\Delta$M$_q$ | 9.05 | | 1.84 | 47.24 | | 6.91 | 1.54 | | 1.46 | 1.34 | | 1.09 | 2.39 | | 4.37 |
| $\Delta$Retail$_q$ | 1.21 | | 0.62 | 1.62 | | 3.16 | 2.16 | | 37.83 | 7.46 | | 2.07 | 1.69 | | 3.11 |
| $\Delta$TradeBal$_q$ | 7.12 | | 4.24 | 1.01 | | 3.91 | 2.64 | | 11.89 | 1.37 | | 5.87 | 1.58 | | 6.48 |
| $\Delta$M$_b$ | 2.15 | | 9.15 | 0.94 | | 0.93 | 12.47 | | 1.83 | 2.45 | | 2.44 | 71.73 | | 6.16 |
| $\Delta$Retail$_b$ | 6.11 | | 23.60 | 2.87 | | 2.25 | 15.62 | | 1.01 | 2.72 | | 39.44 | 2.28 | | 4.11 |
| $\Delta$TradeBal$_b$ | 52.83 | | 8.61 | 3.48 | | 8.91 | 1.56 | | 1.19 | 3.29 | | 5.06 | 59.53 | | 3.93 |
| $\Delta$Oil | 14.06 | | 17.34 | 5.43 | | 44.14 | 0.80 | | 0.92 | 0.99 | | 1.36 | 0.97 | | 0.67 |
| OF | | 0.16 | 0.35 | | 0.25 | 0.33 | | 0.46 | 0.46 | | 0.33 | 0.33 | | 0.24 | 0.31 |
| adj.$R^2$ | 4.30 | 0.22 | 0.77 | 0.87 | 0.18 | 0.31 | 0.47 | 0.87 | 0.42 | 21.26 | 0.64 | 0.59 | 0.55 | 0.35 | 0.35 |
| B: t-statistics | | | | | | | | | | | | | | | |
| $\Delta$IntRate$^{diff}$ | 23.66 | | 1.78 | 0.64 | | 1.20 | 1.11 | | 4.19 | 15.06 | | 4.55 | 0.97 | | 1.23 |
| $\Delta$Slope$^{diff}$ | 1.67 | | 4.04 | 0.35 | | 0.46 | 0.69 | | 1.40 | 6.06 | | 26.63 | 2.26 | | 8.49 |
| $\Delta$Equity$^{diff}$ | 0.65 | | 0.51 | 0.72 | | 7.15 | 0.43 | | 0.40 | 5.38 | | 4.05 | 15.65 | | 98.74 |
| Inflation$^{diff}$ | 0.70 | | 1.49 | 1.26 | | 4.03 | 2.00 | | 1.58 | 2.11 | | 3.46 | 4.53 | | 10.36 |
| $\Delta$M$_q$ | 11.97 | | 1.81 | 21.66 | | 357.82 | 1.35 | | 1.37 | 1.29 | | 1.26 | 2.17 | | 3.04 |
| $\Delta$Retail$_q$ | 1.28 | | 0.62 | 1.22 | | 2.81 | 1.79 | | 4.97 | 64.17 | | 2.10 | 1.39 | | 2.49 |
| $\Delta$TradeBal$_q$ | 7.48 | | 9.01 | 1.22 | | 12.19 | 2.70 | | 50.79 | 1.34 | | 7.31 | 1.76 | | 23.42 |
| $\Delta$M$_b$ | 2.94 | | 3.75 | 0.95 | | 0.90 | 9.37 | | 1.87 | 2.73 | | 2.48 | 10.19 | | 11.65 |
| $\Delta$Retail$_b$ | 102.22 | | 5.98 | 3.00 | | 2.28 | 6.39 | | 0.98 | 2.47 | | 6.64 | 2.22 | | 4.48 |
| $\Delta$TradeBal$_b$ | 4.57 | | 7.67 | 1.92 | | 16.17 | 1.77 | | 1.26 | 3.07 | | 3.04 | 36.84 | | 3.01 |
| $\Delta$Oil | 6.43 | | 16.30 | 5.27 | | 16.87 | 0.89 | | 1.02 | 1.03 | | 1.83 | 0.88 | | 0.55 |
| OF | | 0.14 | 0.24 | | 0.16 | 0.26 | | 0.56 | 0.45 | | 0.48 | 0.43 | | 0.29 | 0.38 |

Table 8: Coefficients of variation of rolling slope coefficients and rolling t-statistics: Spot-return regressions, truncated sample

Notes: Table reports coefficients of variation (absolute value of standard deviation divided by mean) of rolling slope coefficients (panel A) and t-statistics (panel B) for each variable resulting from rolling regressions of different model specifications. The last line of panel A, labelled "adj.$R^2$, reports the coefficients of variation of the sequence of adjusted $R^2$ from the rolling regressions. See notes to Table 2 for variable definitions and regression specifications. Sample starts in January 1999 and ends in December 2007 for all currency pairs

| | $/€ | | | ¥/$ | | | £/$ | | | SEK/€ | | | NOK/€ | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | M | OF | M-OF | M | OF | M-OF | M | OF | M-OF | M | OF | M-OF | M | OF | MOF |
| A: Slope coefficients | | | | | | | | | | | | | | | |
| $\Delta$IntRate$^{diff}$ | 91.57 | | 0.18 | 0.79 | | 1.41 | 2.45 | | 2.90 | 6.52 | | 8.84 | 0.47 | | -0.93 |
| $\Delta$Slope$^{diff}$ | 2.75 | | 13.17 | 0.64 | | 0.76 | 0.83 | | 1.04 | 12.25 | | 4.83 | 0.84 | | -1.59 |
| $\Delta$Equity$^{diff}$ | 0.71 | | 0.65 | 0.90 | | 8.20 | 0.50 | | 0.55 | 1.10 | | 1.43 | 3.90 | | -14.44 |
| Inflation$^{diff}$ | 2.75 | | 140.67 | 1.73 | | 9.95 | 1.49 | | 1.26 | 17.67 | | 4.14 | 5.95 | | -4.30 |
| $\Delta$M$_q$ | 32.20 | | 3.44 | 6.77 | | 19.95 | 2.23 | | 2.59 | 2.98 | | 1.86 | 10.82 | | -13.02 |
| $\Delta$Retail$_q$ | 13.15 | | 27.43 | 3.46 | | 11.12 | 54.46 | | 2.05 | 2.22 | | 79.99 | 2.12 | | -52.62 |
| $\Delta$TradeBal$_q$ | 9.98 | | 8.44 | 1.77 | | 18.19 | 2.23 | | 4.18 | 4.05 | | 11.87 | 17.67 | | 2.66 |
| $\Delta$M$_b$ | 2.02 | | 4.90 | 0.91 | | 1.48 | 38.27 | | 2.49 | 17.67 | | 8.57 | 3.31 | | 31.74 |
| $\Delta$Retail$_b$ | 13.15 | | 27.43 | 1.72 | | 1.44 | 2.69 | | 2.00 | 2.08 | | 4.13 | 1.17 | | 2.41 |
| $\Delta$TradeBal$_b$ | 9.98 | | 5.54 | 40.95 | | 2.33 | 1.57 | | 4.20 | 2.30 | | 11.87 | 4.07 | | 39.30 |
| $\Delta$Oil | 5.68 | | 5.93 | 4.49 | | 985.34 | 1.30 | | 1.90 | 2.47 | | 3.58 | 1.26 | | -0.99 |
| OF | | 0.78 | 0.55 | | 0.30 | 0.74 | | 0.51 | 0.57 | | 0.51 | 0.50 | | 0.29 | 0.50 |
| adj.$R^2$ | 20.80 | 0.52 | 1.68 | 1.07 | 0.25 | 0.41 | 0.64 | 0.97 | 0.61 | 1.37 | 0.74 | 0.77 | 1.17 | 0.44 | 0.67 |
| B: t-statistics | | | | | | | | | | | | | | | |
| $\Delta$IntRate$^{diff}$ | 8.95 | | 2.13 | 0.80 | | 1.24 | -2.06 | | 2.71 | -20.57 | | -8.77 | 0.55 | | 0.90 |
| $\Delta$Slope$^{diff}$ | 2.84 | | 7.45 | 0.45 | | 0.52 | -0.93 | | 1.07 | -9.76 | | 129.78 | 0.81 | | 1.51 |
| $\Delta$Equity$^{diff}$ | 0.75 | | 0.71 | 0.98 | | 18.24 | 0.43 | | 0.59 | -0.98 | | -1.63 | 4.61 | | 7.45 |
| Inflation$^{diff}$ | 2.11 | | 4.71 | 1.72 | | 192.22 | -1.45 | | 1.25 | -7.28 | | 5.46 | 8.19 | | 4.09 |
| $\Delta$M$_q$ | 15.07 | | 2.82 | 5.12 | | 8.77 | 2.37 | | 3.30 | 2.52 | | 1.79 | 6.84 | | 4.78 |
| $\Delta$Retail$_q$ | 0.64 | | 1.46 | 2.45 | | 4.38 | -18.22 | | 2.39 | 2.00 | | -15.67 | 1.85 | | 7.71 |
| $\Delta$TradeBal$_q$ | 4.86 | | 21.19 | 2.40 | | 8.97 | 2.34 | | 20.39 | 2.87 | | -21.36 | 18.64 | | 2.44 |
| $\Delta$M$_b$ | 2.49 | | 22.68 | 0.98 | | 1.41 | 14.61 | | 2.45 | -27.53 | | -5.99 | 2.69 | | 14.90 |
| $\Delta$Retail$_b$ | 17.55 | | 14.27 | 1.56 | | 1.18 | -2.28 | | 1.63 | 2.30 | | 2.92 | 1.06 | | 1.95 |
| $\Delta$TradeBal$_b$ | 314.14 | | 120.21 | 6.86 | | 1.18 | 1.59 | | 4.38 | -1.56 | | -1.43 | 3.43 | | 6.35 |
| $\Delta$Oil | 3.80 | | 6.16 | 4.40 | | 3.17 | -2.10 | | 2.53 | -2.76 | | -5.05 | 1.21 | | 0.97 |
| OF | | 0.35 | 0.57 | | 0.22 | 0.53 | | 0.65 | 0.73 | | 0.60 | 0.50 | | 0.38 | 0.52 |

Table 9: Coefficients of variation of rolling slope coefficients and rolling t-statistics: Order flow regressions, full sample

Notes: Table reports coefficients of variation (absolute value of standard deviation divided by mean) of rolling slope coefficients (panel A) and t-statistics (panel B) for each variable resulting from rolling regressions of different model specifications. The last line of panel A, labelled "adj.$R^2$, reports the coefficients of variation of the sequence of adjusted $R^2$ from the rolling regressions. See notes to Table 2 for variable definitions and regression specifications. Sample start in January 1999 for all currency pairs, and end in December 2007 for $/€ and ¥/$ and in November 2011 for the others.

| | A: Coefficients | | | | | B: t-statistics | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $/€ | ¥/$ | £/$ | SEK/€ | NOK/€ | $/€ | ¥/$ | £/$ | SEK/€ | NOK/€ |
| $\Delta$IntRate$^{diff}$ | 1.16 | 0.86 | 1.08 | 16.95 | 0.77 | 1.12 | 0.80 | 1.07 | 13.39 | 0.84 |
| $\Delta$Slope$^{diff}$ | 2.32 | 0.61 | 1.22 | 10.66 | 0.52 | 1.69 | 0.32 | 1.19 | 6.12 | 0.63 |
| $\Delta$Equity$^{diff}$ | 1.36 | 0.49 | 2.26 | 5.83 | 4.94 | 1.57 | 0.29 | 3.12 | 16.97 | 13.35 |
| Inflation$^{diff}$ | 0.67 | 0.77 | 3.39 | 1.83 | 4.19 | 0.66 | 0.71 | 4.38 | 1.62 | 2.47 |
| $\Delta$M$_q$ | 2.20 | 3.66 | 18.74 | 295.77 | 2.06 | 1.40 | 20.57 | 11.61 | 6.49 | 2.32 |
| $\Delta$Retail$_q$ | 0.58 | 0.92 | 1.18 | 2.25 | 59.90 | 0.63 | 0.85 | 1.01 | 1.92 | 17.71 |
| $\Delta$TradeBal$_q$ | 5.38 | 0.67 | 1.57 | 2.00 | 0.73 | 3.22 | 0.66 | 1.36 | 2.31 | 0.69 |
| $\Delta$M$_b$ | 0.93 | 21.05 | 1.32 | 135.38 | 2.63 | 1.04 | 3.69 | 1.42 | 8.06 | 2.58 |
| $\Delta$Retail$_b$ | 0.09 | 7.94 | 1.10 | 2.44 | 1.68 | 3.99 | 31.04 | 1.00 | 3.07 | 1.39 |
| $\Delta$TradeBal$_b$ | 9.07 | 1.57 | 4.38 | 3.63 | 2.01 | 8.89 | 1.54 | 7.04 | 4.44 | 2.72 |
| $\Delta$Oil | 3.02 | 6.37 | 0.90 | 2.06 | 1.74 | 4.23 | 3.01 | 1.04 | 3.04 | 1.43 |
| adj.$R^2$ | 1.76 | 0.49 | 3.90 | 12.85 | 1.06 | | | | | |

Table 10: Coefficients of variation of rolling slope coefficients and rolling t-statistics: Order flow regressions, truncated sample

Notes: Table reports coefficients of variation (absolute value of standard deviation divided by mean) of rolling slope coefficients (panel A) and t-statistics (panel B) for each variable resulting from rolling regressions of different model specifications. The last line of panel A, labelled "adj.$R^2$, reports the coefficients of variation of the sequence of adjusted $R^2$ from the rolling regressions. See notes to Table 2 for variable definitions and regression specifications. Sample starts in January 1999 and ends in December 2007 for all currency pairs

| | A: Coefficients | | | | | B: t-statistics | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $/€ | ¥/$ | £/$ | SEK/€ | NOK/€ | $/€ | ¥/$ | £/$ | SEK/€ | NOK/€ |
| $\Delta$IntRate$^{diff}$ | 1.01 | 1.03 | 2.39 | 3.79 | 0.52 | 1.05 | 0.89 | 2.42 | 8.68 | 0.52 |
| $\Delta$Slope$^{diff}$ | 1.10 | 0.89 | 2.33 | 1.94 | 0.62 | 0.99 | 0.63 | 2.86 | 2.19 | 0.58 |
| $\Delta$Equity$^{diff}$ | 2.42 | 0.56 | 2.19 | 6.03 | 3.06 | 3.38 | 0.45 | 2.97 | 8.97 | 6.35 |
| Inflation$^{diff}$ | 1.07 | 0.98 | 13.54 | 3.63 | 117.02 | 1.08 | 0.93 | 35.96 | 2.49 | 3.98 |
| $\Delta$M$_q$ | 3.10 | 2.21 | 3.01 | 2.31 | 387.42 | 1.89 | 7.08 | 3.30 | 2.06 | 5.40 |
| $\Delta$Retail$_q$ | 1.22 | 1.12 | 3.19 | 1.95 | 1.52 | 1.00 | 1.18 | 2.89 | 1.39 | 2.55 |
| $\Delta$TradeBal$_q$ | 0.57 | 1.24 | 6.89 | 1.76 | 1.28 | 4.46 | 1.36 | 3.02 | 1.95 | 1.22 |
| $\Delta$M$_b$ | 2.94 | 643.47 | 2.08 | 4.50 | 2.66 | 2.33 | 18.20 | 2.39 | 7.03 | 1.69 |
| $\Delta$Retail$_b$ | 4.02 | 6.43 | 3.60 | 3.37 | 0.87 | 4.50 | 7.14 | 3.41 | 6.33 | 0.72 |
| $\Delta$TradeBal$_b$ | 3.66 | 2.36 | 1.76 | 2.48 | 1.83 | 8.26 | 2.76 | 1.75 | 2.33 | 2.73 |
| $\Delta$Oil | 2.48 | 4.41 | 1.93 | 2.99 | 4.94 | 2.98 | 2.50 | 2.51 | 6.06 | 2.13 |
| adj.$R^2$ | 2.63 | 0.68 | 25.44 | 4.64 | 3.55 | | | | | |

Table 11: Correlation coefficients of rolling slope coefficients and t-statistics resulting from rolling regressions of M and OF-DV specifications, full sample

Notes: Table reports the correlation coefficients of rolling slope coefficients and t-statistics for each macro variable that result from rolling regressions of M and OF-DV specifications where spot returns and order flow are regressed on the same set of macro variables. See notes to Table 2 for variable definitions and regression specifications. Sample start in January 1999 for all currency pairs, and end in December 2007 for $/€ and ¥/$ and in November 2011 for the others.

| | $/€ | | ¥/$ | | £/$ | | SEK/€ | | NOK/€ | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coeff | t-stat. | Coeff | t-stat. | Coeff | t-stat. | Coeff | t-stat. | Coeff | t-stat. |
| $\Delta$IntRate$^{diff}$ | 0.00 | 0.19 | 0.39 | 0.56 | 0.29 | 0.30 | 0.68 | 0.47 | 0.68 | 0.90 |
| | (1.00) | (0.11) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| $\Delta$Slope$^{diff}$ | 0.403 | 0.423 | 0.861 | 0.500 | 0.035 | 0.199 | 0.454 | 0.347 | 0.053 | 0.431 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.75) | (0.07) | (0.00) | (0.00) | (0.63) | (0.00) |
| $\Delta$Equity$^{diff}$ | 0.96 | 0.90 | 0.50 | 0.54 | 0.58 | 0.64 | 0.60 | 0.55 | 0.92 | 0.90 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Inflation$^{diff}$ | 0.07 | -0.20 | 0.56 | 0.67 | 0.45 | 0.43 | 0.45 | 0.47 | 0.79 | 0.72 |
| | (0.56) | (0.09) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| $\Delta$M$_q$ | 0.58 | 0.48 | 0.91 | 0.90 | 0.46 | 0.47 | 0.66 | 0.29 | 0.81 | 0.71 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| $\Delta$Retail$_q$ | 0.19 | 0.28 | 0.76 | 0.55 | 0.51 | 0.57 | 0.79 | 0.82 | 0.01 | -0.06 |
| | (0.11) | (0.02) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.90) | (0.51) |
| $\Delta$TradeBal$_q$ | 0.27 | 0.28 | 0.78 | 0.65 | 0.15 | 0.04 | 0.28 | 0.34 | 0.65 | 0.69 |
| | (0.02) | (0.02) | (0.00) | (0.00) | (0.11) | (0.68) | (0.00) | (0.00) | (0.00) | (0.00) |
| $\Delta$M$_b$ | 0.20 | 0.48 | 0.63 | 0.74 | 0.70 | 0.61 | 0.44 | 0.29 | 0.67 | 0.66 |
| | (0.09) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| $\Delta$Retail$_b$ | 0.78 | 0.78 | 0.49 | 0.44 | 0.66 | 0.68 | 0.59 | 0.49 | 0.83 | 0.73 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| $\Delta$TradeBal$_b$ | 0.78 | 0.55 | 0.91 | 0.90 | 0.85 | 0.87 | 0.62 | 0.63 | 0.68 | 0.57 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| $\Delta$Oil | 0.94 | 0.95 | 0.88 | 0.94 | 0.73 | 0.72 | 0.49 | 0.49 | 0.94 | 0.91 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| adj.$R^2$ | 0.26 | | 0.37 | | 0.51 | | 0.10 | | 0.61 | |
| | (0.03) | | (0.00) | | (0.00) | | (0.28) | | (0.00) | |

Table 12: Correlation coefficients of rolling slope coefficients and t-statistics resulting from rolling regressions of M and OF-DV specifications, truncated sample

Notes: Table reports the correlation coefficients of rolling slope coefficients and t-statistics for each macro variable that result from rolling regressions of M and OF-DV specifications where spot returns and order flow are regressed on the same set of macro variables. See notes to Table 2 for variable definitions and regression specifications. Sample start in January 1999 and end in December 2007 for all currency pairs.

| | $/€ | | ¥/$ | | £/$ | | SEK/€ | | NOK/€ | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coeff | t-stat. | Coeff | t-stat. | Coeff | t-stat. | Coeff | t-stat. | Coeff | t-stat. |
| $\Delta$IntRate$^{diff}$ | 0.276 | 0.415 | 0.489 | 0.485 | 0.403 | 0.540 | 0.719 | 0.493 | 0.414 | 0.631 |
| | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| $\Delta$Slope$^{diff}$ | 0.403 | 0.423 | 0.861 | 0.500 | 0.035 | 0.199 | 0.454 | 0.347 | 0.053 | 0.431 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.75) | (0.07) | (0.00) | (0.00) | (0.63) | (0.00) |
| $\Delta$Equity$^{diff}$ | 0.675 | 0.567 | 0.016 | 0.330 | 0.499 | 0.520 | 0.354 | -0.042 | 0.636 | 0.618 |
| | (0.00) | (0.00) | (0.88) | (0.00) | (0.00) | (0.00) | (0.00) | (0.71) | (0.00) | (0.00) |
| Inflation$^{diff}$ | 0.310 | 0.237 | 0.320 | 0.306 | 0.296 | 0.264 | 0.725 | 0.732 | 0.399 | 0.484 |
| | (0.00) | (0.03) | (0.00) | (0.00) | (0.01) | (0.02) | (0.00) | (0.00) | (0.00) | (0.00) |
| $\Delta$M$_q$ | 0.602 | 0.435 | 0.872 | 0.832 | 0.706 | 0.756 | 0.344 | 0.235 | 0.303 | 0.173 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.03) | (0.01) | (0.12) |
| $\Delta$Retail$_q$ | 0.677 | 0.236 | 0.420 | 0.491 | 0.712 | 0.612 | 0.679 | 0.677 | 0.194 | -0.036 |
| | (0.00) | (0.03) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.08) | (0.75) |
| $\Delta$TradeBal$_q$ | -0.275 | -0.142 | 0.757 | 0.628 | 0.173 | 0.015 | 0.302 | 0.285 | 0.397 | 0.252 |
| | (0.01) | (0.20) | (0.00) | (0.00) | (0.12) | (0.89) | (0.01) | (0.01) | (0.00) | (0.02) |
| $\Delta$M$_b$ | 0.561 | 0.574 | 0.407 | 0.524 | 0.586 | 0.363 | 0.785 | 0.654 | 0.755 | 0.549 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| $\Delta$Retail$_b$ | 0.140 | 0.732 | 0.714 | 0.728 | 0.723 | 0.604 | 0.504 | 0.440 | 0.662 | 0.393 |
| | (0.20) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| $\Delta$TradeBal$_b$ | 0.534 | 0.403 | 0.900 | 0.839 | 0.702 | 0.727 | 0.282 | 0.596 | 0.474 | 0.496 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.01) | (0.00) | (0.00) | (0.00) |
| $\Delta$Oil | 0.836 | 0.849 | 0.843 | 0.865 | 0.459 | 0.507 | 0.770 | 0.638 | 0.754 | 0.795 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| adj.$R^2$ | 0.41 | | 0.26 | | 0.18 | | 0.34 | | 0.06 | |
| | (0.00) | | (0.02) | | (0.09) | | (0.00) | | (0.56) | |

Table 13: Spot return and Macro-generated order flow, full sample

Notes: OLS coefficient-estimates. In all specifications spot return (the first natural log difference of spot exchange rate over a month) is the dependent variable. $OF^{MACRO}$ is macro induced order flow predicted by rolling regressions (36 month window size) of order flow on the set of macro variables. $OF^{RESID}$ is order flow residuals computed as the difference between actual and predicted order flow. $OF^{MACRO}_{UNSTABLE}$ is the unstable part of macro Induced order flow; that is, the residuals of the regression of macro induced order flow ($OF^{MACRO}$) on the set of macro variables. $OF^{MACRO}_{STABLE}$ is the stable part of macro induced order flow; that is, the fitted values of the regression of $OF^{MACRO}$ on the set of macro variables. Column Macro denotes if the set of macro variables are used as controls. t-statistics in parentheses based on bootstrapped standard errors (10000 repetitions). Boldface denotes significance at, at least, 10%-level. Sample start in January 1999 for all currency pairs, and end in December 2007 for $/€ and ¥/$ and in November 2011 for the others.

| | | $OF^{RESID}$ | | $OF^{MACRO}$ | | $OF^{MACRO}_{UNSTABLE}$ | | $OF^{MACRO}_{STABLE}$ | | Macro | Adj.$R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | | |
| $/€ | OFM-1 | **0.129** | (4.81) | **0.096** | (2.58) | | | | | | 0.24 |
| | OFM-2 | **0.128** | (4.88) | | | 0.085 | (1.61) | **0.105** | (2.14) | | 0.23 |
| | OFM-3 | **0.113** | (4.45) | 0.075 | (1.57) | | | | | y | 0.30 |
| | OFM-4 | **0.100** | (4.05) | | | | | | | y | 0.28 |
| | M | | | | | | | | | y | 0.14 |
| ¥/$ | OFM-1 | **0.129** | (6.72) | **0.138** | (4.79) | | | | | | 0.40 |
| | OFM-2 | **0.123** | (6.13) | | | **0.107** | (2.40) | **0.154** | (4.47) | | 0.39 |
| | OFM-3 | **0.139** | (5.78) | **0.126** | (2.72) | | | | | y | 0.44 |
| | OFM-4 | **0.100** | (4.94) | | | | | | | y | 0.38 |
| | M | | | | | | | | | y | 0.13 |
| £/$ | OFM-1 | **0.647** | (5.45) | **0.524** | (3.79) | | | | | | 0.19 |
| | OFM-2 | **0.696** | (5.96) | | | **0.844** | (4.71) | 0.245 | (1.44) | | 0.23 |
| | OFM-3 | **0.560** | (6.56) | **0.728** | (5.71) | | | | | y | 0.57 |
| | OFM-4 | **0.286** | (3.60) | | | | | | | y | 0.46 |
| | M | | | | | | | | | y | 0.40 |
| SEK/€ | OFM-1 | **1.707** | (6.05) | **2.330** | (5.09) | | | | | | 0.23 |
| | OFM-2 | **1.545** | (5.43) | | | **1.649** | (3.14) | **3.671** | (5.31) | | 0.27 |
| | OFM-3 | **1.700** | (6.39) | **1.836** | (3.79) | | | | | y | 0.34 |
| | OFM-4 | **1.029** | (4.85) | | | | | | | y | 0.26 |
| | M | | | | | | | | | y | 0.12 |
| NOK/€ | OFM-1 | **2.101** | (7.39) | **2.897** | (7.08) | | | | | | 0.36 |
| | OFM-2 | **1.718** | (6.12) | | | **1.544** | (3.15) | **4.690** | (8.18) | | 0.44 |
| | OFM-3 | **1.723** | (6.69) | **1.549** | (3.43) | | | | | y | 0.50 |
| | OFM-4 | **1.231** | (5.53) | | | | | | | y | 0.45 |
| | M | | | | | | | | | y | 0.32 |

Table 14: Spot return and Macro-generated order flow, truncated sample

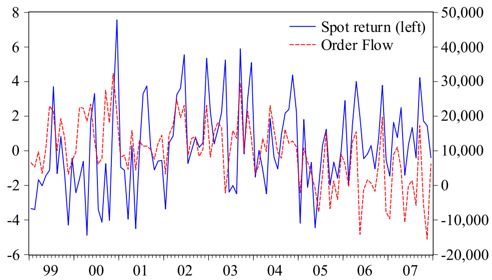
Notes: OLS coefficient-estimates. In all specifications spot return (the first natural log difference of spot exchange rate over a month) is the dependent variable. $OF^{MACRO}$ is macro induced order flow predicted by rolling regressions (36 month window size) of order flow on the set of macro variables. $OF^{RESID}$ is order flow residuals computed as the difference between actual and predicted order flow. $OF^{MACRO}_{UNSTABLE}$ is the unstable part of macro Induced order flow; that is, the residuals of the regression of macro induced order flow ($OF^{MACRO}$) on the set of macro variables. $OF^{MACRO}_{STABLE}$ is the stable part of macro induced order flow; that is, the fitted values of the regression of $OF^{MACRO}$ on the set of macro variables. Column Macro denotes if the set of macro variables are used as controls. t-statistics in parentheses based on bootstrapped standard errors (10000 repetitions). Boldface denotes significance at, at least, 10%-level. Sample start in January 1999 and end in December 2007 for all currency pairs.

| | | $OF^{RESID}$ | | $OF^{MACRO}$ | | $OF^{MACRO}_{UNSTABLE}$ | | $OF^{MACRO}_{STABLE}$ | | Macro | Adj.$R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | | |
| \$/€ | OFM-1 | **0.119** | (4.61) | **0.133** | (3.60) | | | | | | 0.20 |
| | OFM-2 | **0.113** | (4.29) | | | **0.109** | (2.37) | **0.170** | (3.03) | | 0.20 |
| | OFM-3 | **0.108** | (4.26) | **0.104** | (2.49) | | | | | y | 0.27 |
| | OFM-4 | **0.071** | (3.34) | | | | | | | y | 0.23 |
| | M | | | | | | | | | y | 0.10 |
| ¥/\$ | OFM-1 | **0.151** | (7.44) | **0.151** | (5.42) | | | | | | 0.40 |
| | OFM-2 | **0.138** | (6.50) | | | **0.107** | (2.83) | **0.197** | (5.18) | | 0.41 |
| | OFM-3 | **0.140** | (6.00) | **0.109** | (2.86) | | | | | y | 0.38 |
| | OFM-4 | **0.097** | (5.21) | | | | | | | y | 0.33 |
| | M | | | | | | | | | y | 0.13 |
| £/\$ | OFM-1 | **0.696** | (5.19) | **0.685** | (3.95) | | | | | | 0.24 |
| | OFM-2 | **0.701** | (5.33) | | | **0.662** | (3.76) | **0.820** | (2.44) | | 0.23 |
| | OFM-3 | **0.577** | (5.07) | **0.561** | (3.76) | | | | | y | 0.41 |
| | OFM-4 | **0.305** | (3.18) | | | | | | | y | 0.32 |
| | M | | | | | | | | | y | 0.18 |
| SEK/€ | OFM-1 | **1.610** | (6.97) | **1.422** | (4.16) | | | | | | 0.37 |
| | OFM-2 | **1.700** | (7.04) | | | **1.725** | (4.04) | **1.163** | (2.86) | | 0.37 |
| | OFM-3 | **1.719** | (7.38) | **1.749** | (4.30) | | | | | y | 0.38 |
| | OFM-4 | **0.945** | (5.71) | | | | | | | y | 0.25 |
| | M | | | | | | | | | y | -0.02 |
| NOK/€ | OFM-1 | **2.122** | (7.72) | **2.099** | (5.75) | | | | | | 0.41 |
| | OFM-2 | **1.823** | (6.78) | | | **1.055** | (2.40) | **3.073** | (7.17) | | 0.48 |
| | OFM-3 | **1.556** | (5.85) | **0.764** | (1.80) | | | | | y | 0.49 |
| | OFM-4 | **1.225** | (6.21) | | | | | | | y | 0.48 |
| | M | | | | | | | | | y | 0.16 |

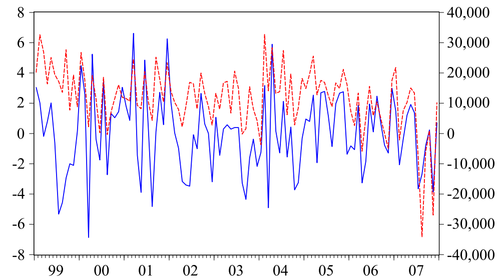
## Figure 1: Spot return and order flow

Notes: "Spot return" (on left axis, solid line) is the one-month difference in log of spot exchange rate (in percentage). "Order Flow" (on right axis, dotted line) is monthly-aggregated order flow. Order flow for EUR/USD and USD/JPY is sourced from EBS, and measured in millions of base currency. The rest of the order flows are from Reuters and measured in number of trades. Spot exchange rates are end-of-month rates from DataStream.

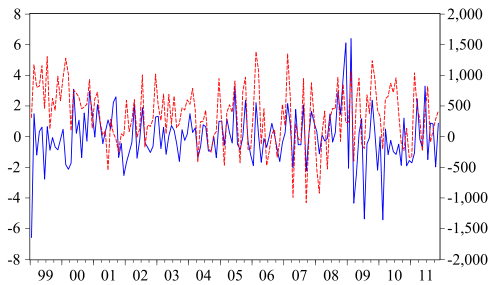
(a) EUR/USD



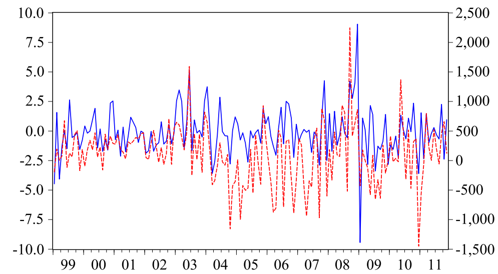

(b) USD/JPY



(c) EUR/SEK



(d) EUR/NOK



(e) GBP/USD

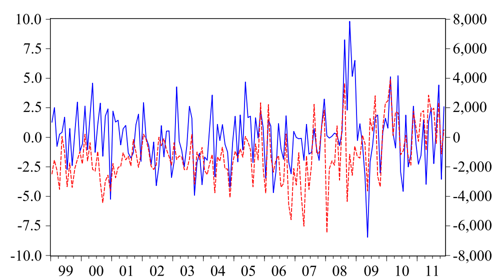


Figure 2: Rolling slope coefficients: EUR/USD 36

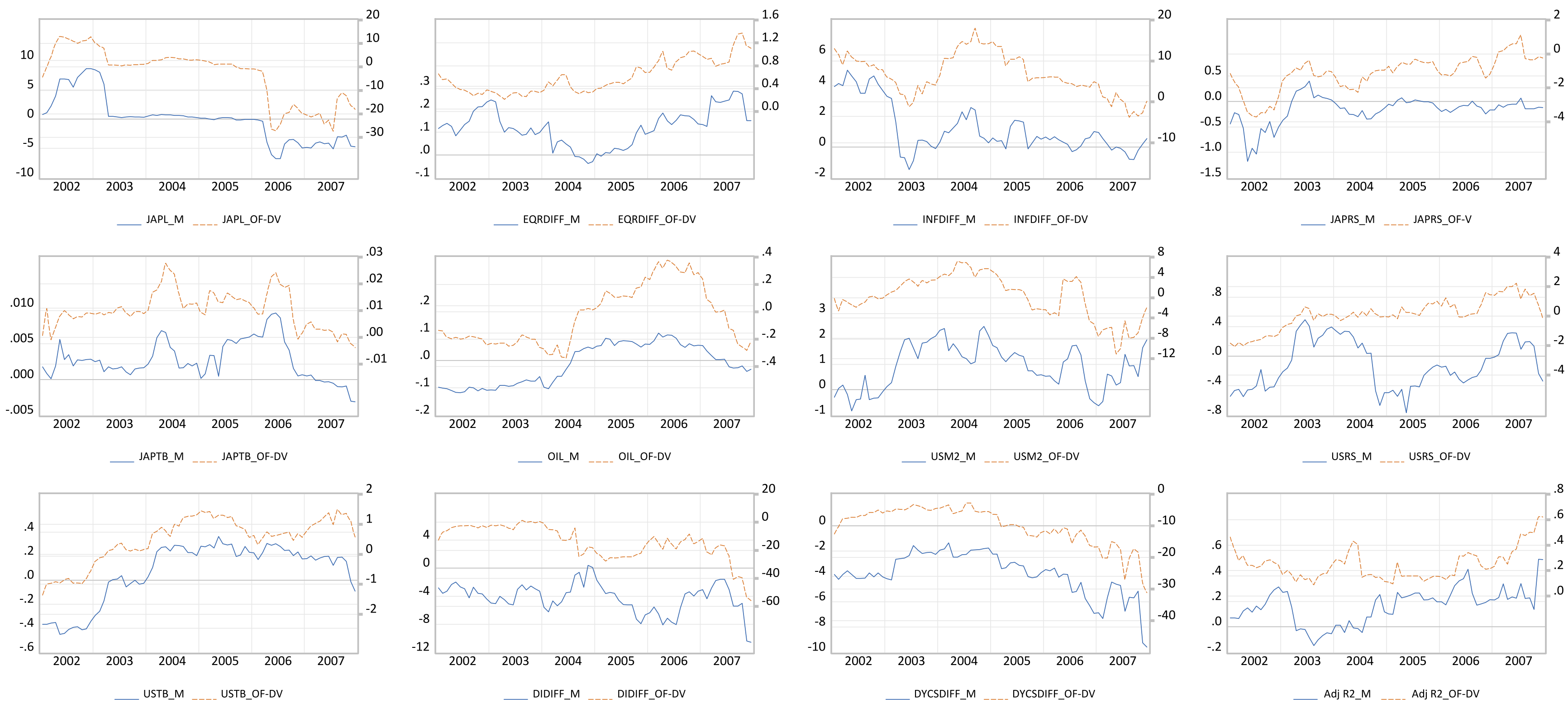
Notes: Figure depicts the rolling slope coefficients of each macro variable that result from the rolling regressions of M and OF-DV specifications where spot returns and order flow are regressed on the same set of macro variables. See notes to Table 2 for variable definitions and regression specifications. The bottom right graph tracks the adj.$R^2$ for the M and OF-DV rolling regressions. M is on left scale. OF-DV is on right scale. Sample period: Jan. 1999 – Dec. 2007. Rolling window size: 36 months.

Figure 3: Rolling slope coefficients: EUR/USD 24

Notes: Figure depicts the rolling slope coefficients of each macro variable that result from the rolling regressions of M and OF-DV specifications where spot returns and order flow are regressed on the same set of macro variables. See notes to Table 2 for variable definitions and regression specifications. The bottom right graph tracks the adj.$R^2$ for the M and OF-DV rolling regressions. M is on left scale. OF-DV is on right scale. Sample period: Jan. 1999 – Dec. 2007. Rolling window size: 24 months.

Figure 4: Rolling slope coefficients: USD/JPY 36

Notes: Figure depicts the rolling slope coefficients of each macro variable that result from the rolling regressions of M and OF-DV specifications where spot returns and order flow are regressed on the same set of macro variables. See notes to Table 2 for variable definitions and regression specifications. The bottom right graph tracks the adj.$R^2$ for the M and OF-DV rolling regressions. M is on left scale. OF-DV is on right scale. Sample period: Jan. 1999 – Dec. 2007. Rolling window size: 36 months.



# Figure 5: Rolling slope coefficients: USD/JPY 24

Notes: Figure depicts the rolling slope coefficients of each macro variable that result from the rolling regressions of M and OF-DV specifications where spot returns and order flow are regressed on the same set of macro variables. See notes to Table 2 for variable definitions and regression specifications. The bottom right graph tracks the adj.$R^2$ for the M and OF-DV rolling regressions. M is on left scale. OF-DV is on right scale. Sample period: Jan. 1999 – Dec. 2007. Rolling window size: 24 months.

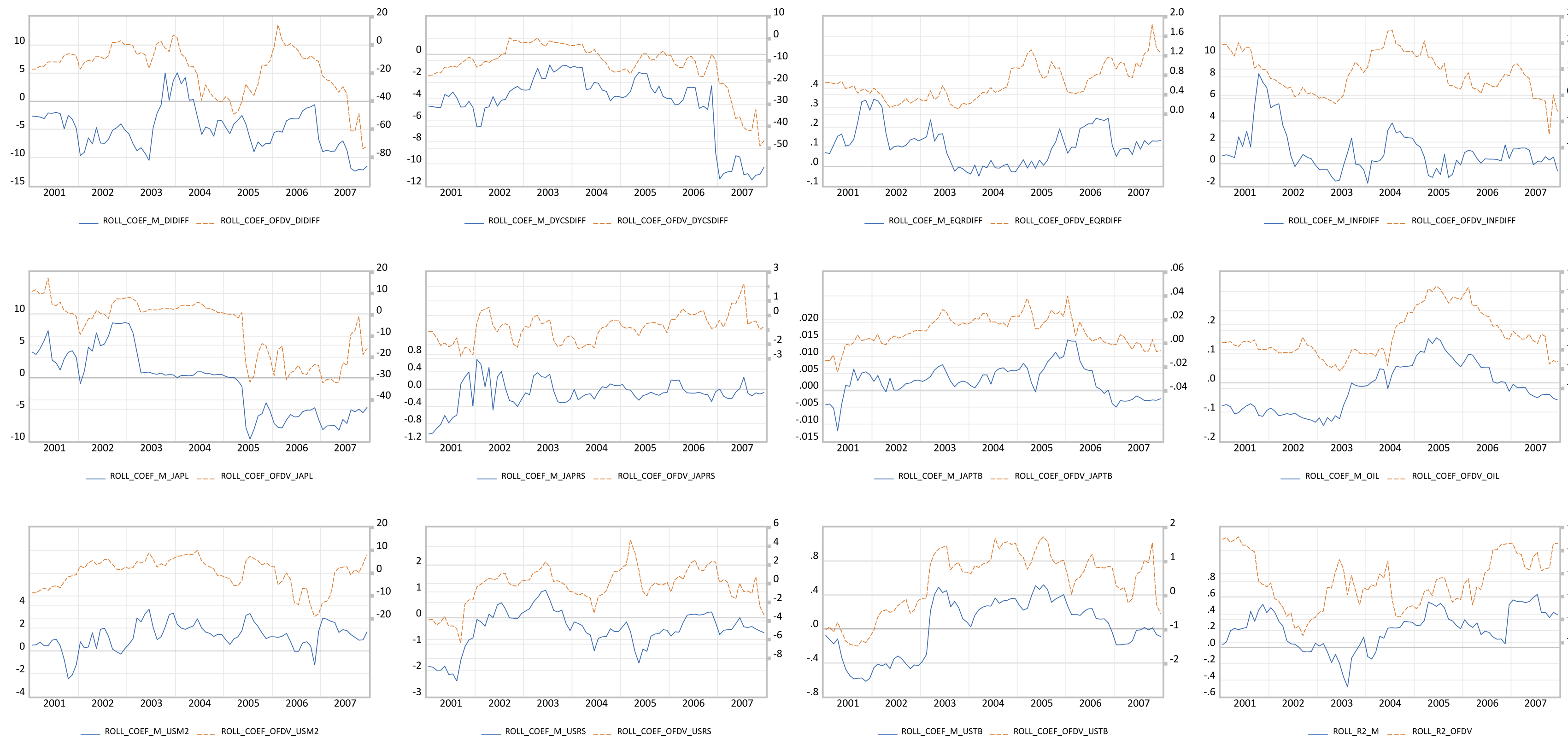
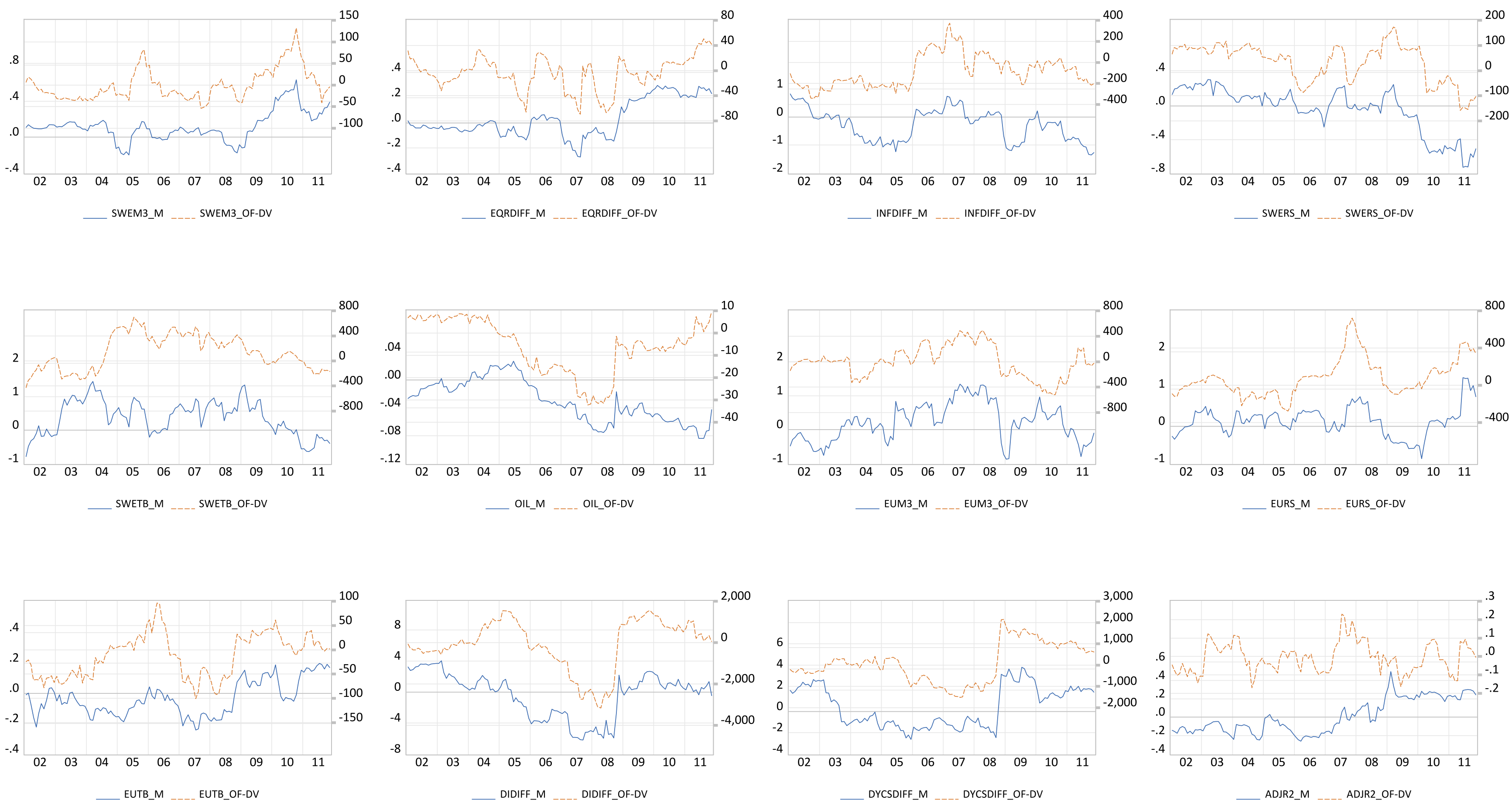


Figure 6: Rolling slope coefficients: EUR/SEK 36

Notes: Figure depicts the rolling slope coefficients of each macro variable that result from the rolling regressions of M and OF-DV specifications where spot returns and order flow are regressed on the same set of macro variables. See notes to Table 2 for variable definitions and regression specifications. The bottom right graph tracks the adj.$R^2$ for the M and OF-DV rolling regressions. M is on left scale. OF-DV is on right scale. Sample period: Jan. 1999 – Nov. 2011. Rolling window size: 36 months.



## Figure 7: Rolling slope coefficients: EUR/SEK 24

Notes: Figure depicts the rolling slope coefficients of each macro variable that result from the rolling regressions of M and OF-DV specifications where spot returns and order flow are regressed on the same set of macro variables. See notes to Table 2 for variable definitions and regression specifications. The bottom right graph tracks the adj.$R^2$ for the M and OF-DV rolling regressions. M is on left scale. OF-DV is on right scale. Sample period: Jan. 1999 – Dec. 2007. Rolling window size: 24 months.

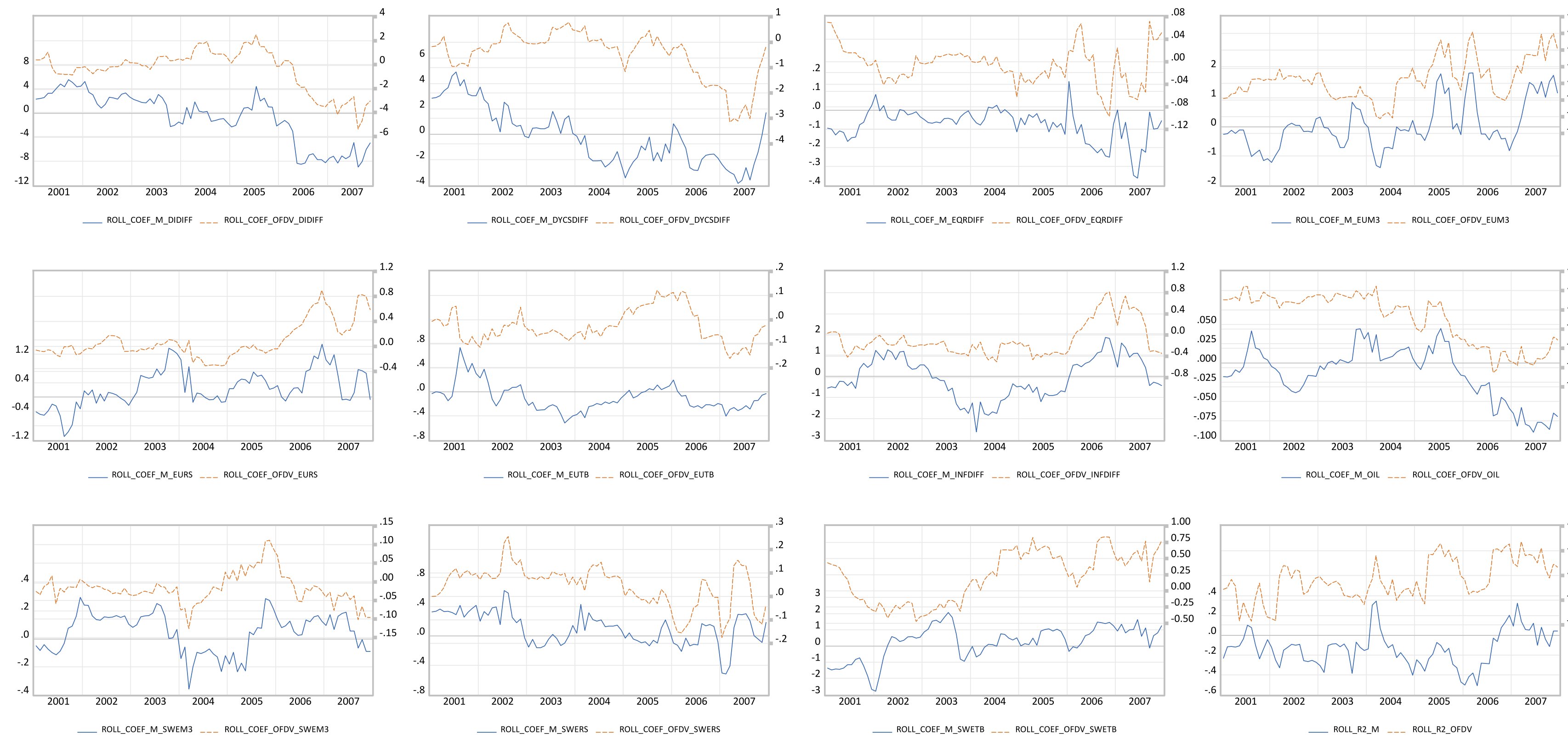
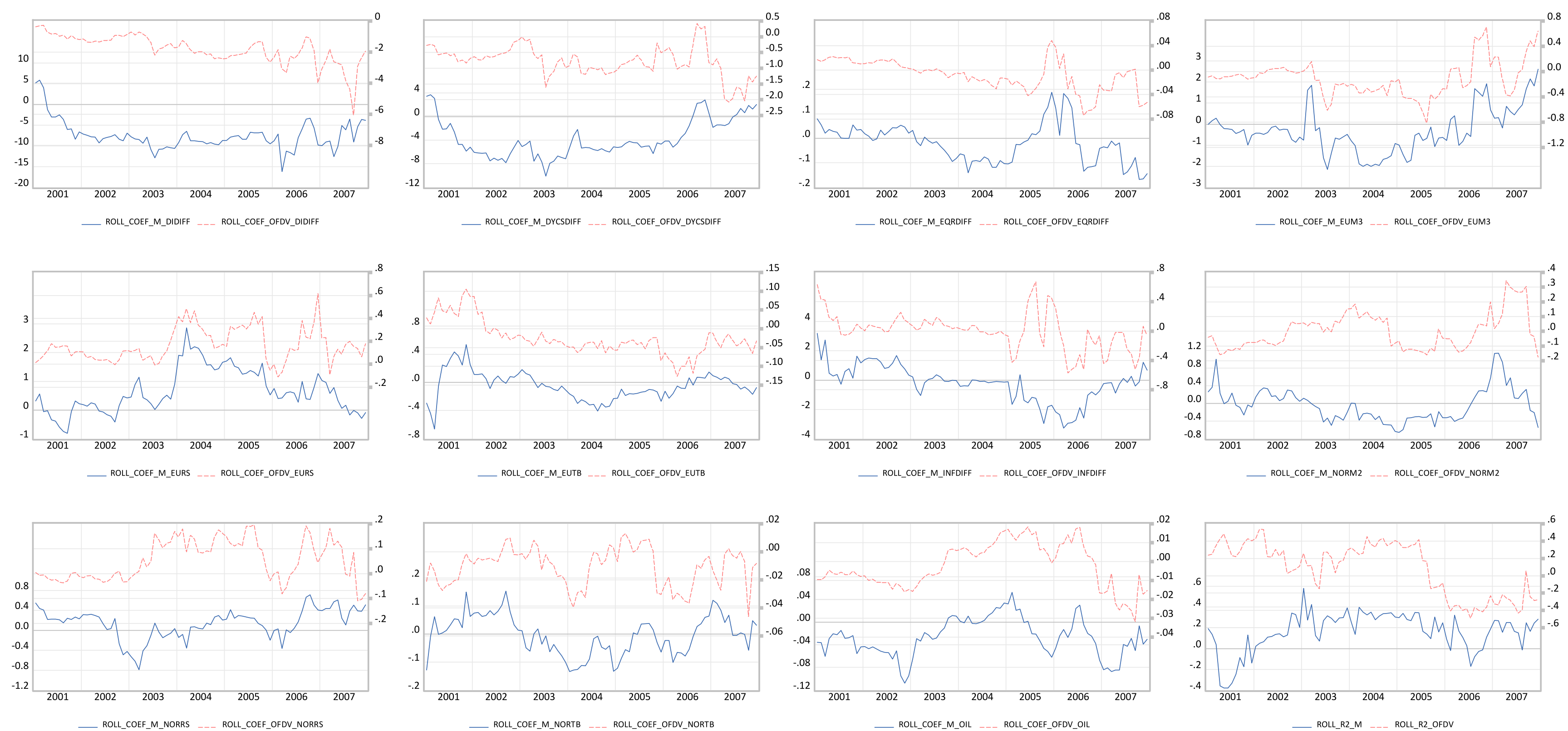


Figure 8: Rolling slope coefficients: EUR/NOK 36

Notes: Figure depicts the rolling slope coefficients of each macro variable that result from the rolling regressions of M and OF-DV specifications where spot returns and order flow are regressed on the same set of macro variables. See notes to Table 2 for variable definitions and regression specifications. The bottom right graph tracks the adj.$R^2$ for the M and OF-DV rolling regressions. M is on left scale. OF-DV is on right scale. Sample period: Jan. 1999 – Nov. 2011. Rolling window size: 36 months.

Figure 9: Rolling slope coefficients: EUR/NOK 24

Notes: Figure depicts the rolling slope coefficients of each macro variable that result from the rolling regressions of M and OF-DV specifications where spot returns and order flow are regressed on the same set of macro variables. See notes to Table 2 for variable definitions and regression specifications. The bottom right graph tracks the adj.$R^2$ for the M and OF-DV rolling regressions. M is on left scale. OF-DV is on right scale. Sample period: Jan. 1999 – Dec. 2007. Rolling window size: 24 months.



# Figure 10: Rolling slope coefficients: GBP/USD 36

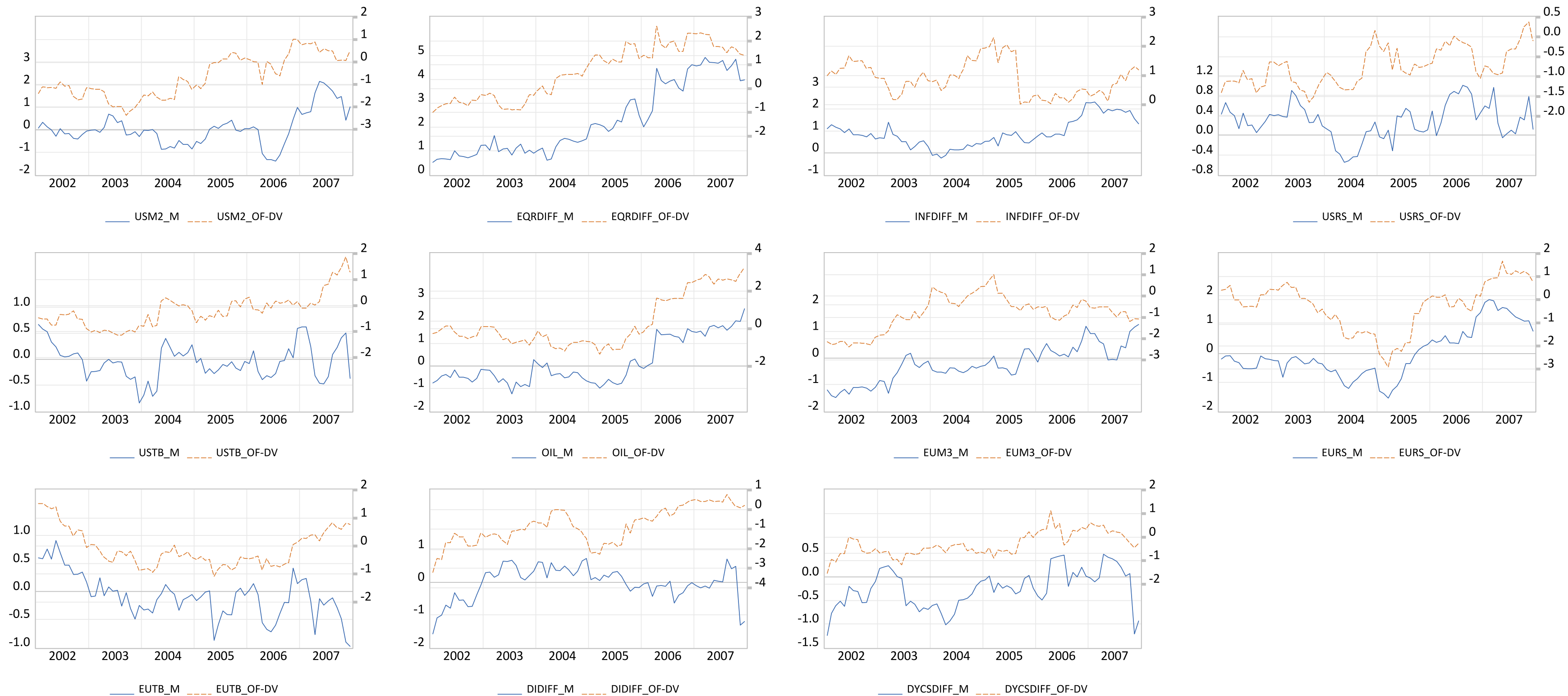
Notes: Figure depicts the rolling slope coefficients of each macro variable that result from the rolling regressions of M and OF-DV specifications where spot returns and order flow are regressed on the same set of macro variables. See notes to Table 2 for variable definitions and regression specifications. The bottom right graph tracks the adj.$R^2$ for the M and OF-DV rolling regressions. M is on left scale. OF-DV is on right scale. Sample period: Jan. 1999 – Nov. 2011. Rolling window size: 36 months.

Figure 11: Rolling slope coefficients: GBP/USD 24

Notes: Figure depicts the rolling slope coefficients of each macro variable that result from the rolling regressions of M and OF-DV specifications where spot returns and order flow are regressed on the same set of macro variables. See notes to Table 2 for variable definitions and regression specifications. The bottom right graph tracks the adj.$R^2$ for the M and OF-DV rolling regressions. M is on left scale. OF-DV is on right scale. Sample period: Jan. 1999 – Dec. 2007. Rolling window size: 24 months.

# Figure 12: Rolling t-statistics: EUR/USD 36

Notes: Figure depicts the rolling t-statistics of each macro variable that result from the rolling regressions of M and OF-DV specifications where spot returns and order flow are regressed on the same set of macro variables. See notes to Table 2 for variable definitions and regression specifications. M is on left scale. OF-DV is on right scale. Sample period: Jan. 1999 – Dec. 2007. Rolling window size: 36 months.



# Figure 13: Rolling t-statistics: EUR/USD 24

Notes: Figure depicts the rolling t-statistics of each macro variable that result from the rolling regressions of M and OF-DV specifications where spot returns and order flow are regressed on the same set of macro variables. See notes to Table 2 for variable definitions and regression specifications. M is on left scale. OF-DV is on right scale. Sample period: Jan. 1999 – Dec. 2007. Rolling window size: 36 months.

Figure 14: Rolling t-statistics: USD/JPY 36

Notes: Figure depicts the rolling t-statistics of each macro variable that result from the rolling regressions of M and OF-DV specifications where spot returns and order flow are regressed on the same set of macro variables. See notes to Table 2 for variable definitions and regression specifications. M is on left scale. OF-DV is on right scale. Sample period: Jan. 1999 – Dec. 2007. Rolling window size: 36 months.

Figure 15: Rolling t-statistics: USD/JPY 24

Notes: Figure depicts the rolling t-statistics of each macro variable that result from the rolling regressions of M and OF-DV specifications where spot returns and order flow are regressed on the same set of macro variables. See notes to Table 2 for variable definitions and regression specifications. M is on left scale. OF-DV is on right scale. Sample period: Jan. 1999 – Dec. 2007. Rolling window size: 24 months.

Figure 16: Rolling t-statistics: EUR/SEK 36

Notes: Figure depicts the rolling t-statistics of each macro variable that result from the rolling regressions of M and OF-DV specifications where spot returns and order flow are regressed on the same set of macro variables. See notes to Table 2 for variable definitions and regression specifications. M is on left scale. OF-DV is on right scale. Sample period: Jan. 1999 – Nov. 2011. Rolling window size: 36 months.

# Figure 17: Rolling t-statistics: EUR/SEK 24

Notes: Figure depicts the rolling t-statistics of each macro variable that result from the rolling regressions of M and OF-DV specifications where spot returns and order flow are regressed on the same set of macro variables. See notes to Table 2 for variable definitions and regression specifications. M is on left scale. OF-DV is on right scale. Sample period: Jan. 1999 – Dec. 2007. Rolling window size: 24 months.

Figure 18: Rolling t-statistics: EUR/NOK 36

Notes: Figure depicts the rolling t-statistics of each macro variable that result from the rolling regressions of M and OF-DV specifications where spot returns and order flow are regressed on the same set of macro variables. See notes to Table 2 for variable definitions and regression specifications. M is on left scale. OF-DV is on right scale. Sample period: Jan. 1999 – Nov. 2011. Rolling window size: 36 months.

Figure 19: Rolling t-statistics: EUR/NOK 24

Notes: Figure depicts the rolling t-statistics of each macro variable that result from the rolling regressions of M and OF-DV specifications where spot returns and order flow are regressed on the same set of macro variables. See notes to Table 2 for variable definitions and regression specifications. M is on left scale. OF-DV is on right scale. Sample period: Jan. 1999 – Dec. 2007. Rolling window size: 24 months.

Figure 20: Rolling t-statistics: GBP/USD 36

Notes: Figure depicts the rolling t-statistics of each macro variable that result from the rolling regressions of M and OF-DV specifications where spot returns and order flow are regressed on the same set of macro variables. See notes to Table 2 for variable definitions and regression specifications. M is on left scale. OF-DV is on right scale. Sample period: Jan. 1999 – Nov. 2011. Rolling window size: 36 months.

Figure 21: Rolling t-statistics: GBP/USD 24

Notes: Figure depicts the rolling t-statistics of each macro variable that result from the rolling regressions of M and OF-DV specifications where spot returns and order flow are regressed on the same set of macro variables. See notes to Table 2 for variable definitions and regression specifications. M is on left scale. OF-DV is on right scale. Sample period: Jan. 1999 – Dec. 2011. Rolling window size: 36 months.

# *Chapter III*

# Commercial Banks' Assets and Future Expected Returns

Anna Lindahl[*] Yacine Hammami[†‡]

## Abstract

Using in-sample and out-of-sample tests and controlling for data mining, we find that the asset growth of commercial banks strongly predicts the excess returns on stocks, bonds, derivatives, and currencies portfolios. The bank asset factor strongly predicts market excess returns even at a weekly frequency. We find clear patterns across assets in the predictive coefficients: they increase in magnitude from government to corporate bonds to options to stocks. This pattern is consistent with the business risks of the assets, and thus supports a risk-based explanation of the predictive power of commercial banks' asset growth. We also find that the bank asset factor possesses strong explanatory power for the cross-section of expected asset returns, which backs up the results of the predictability tests.

*Keywords:* Return predictability; data mining; banks' balance sheets; leverage.

*JEL classification:* C10; C13; G12; G21

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# 1 Introduction

Exploiting information from financial intermediaries' balance sheets to predict asset returns is a novel area of research (Adrian et al., 2014; He et al., 2017; Baron and Muir, 2018). The rationale stems from the literature on financial friction and "institutional finance", in which the behavior of financial intermediaries has a first-order effect on asset prices.[1] The literature has proposed two variants of intermediary asset pricing theories: "equity constraint" models, in which the key state variable is the intermediaries' net worth (He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014) and "debt constraint" models, in which lending (funding liquidity) is the main state variable (Fostel and Geanakoplos, 2008; Adrian and Shin, 2014).

The present paper belongs to the second category. Adrian et al. (2014, 2015) argue that broker-dealer book leverage[2] is a suitable proxy for lending conditions since lower broker-dealer leverage indicates tighter funding constraints, which signals lower funding liquidity to traders and, therefore, future lower asset prices. In our paper, we argue that commercial banks' total assets are a more appropriate measure of funding liquidity than broker-dealer book leverage because it is a direct measure of credit supply to the whole economy, not only to dealers. Thus, changes in commercial banks' assets are expected to be more connected to economic conditions than broker-dealer book leverage, and thus are expected to have a stronger effect on asset prices. The rationale is that lower asset growth in commercial banks implies lower funding for economic agents, thereby leading to lower consumption and investment. The implied weaker economic conditions lead to higher risk premium.

We find, indeed, that lower asset growth of commercial banks strongly predicts higher excess returns on stocks, bonds, derivatives, and currencies portfolios. This finding is

[1] Gromb and Vayanos, 2002; Mitchell et al., 2007; Fostel and Geanakoplos, 2008; Brunnermeier and Pedersen, 2009; Shleifer and Vishny, 2010; Duffie, 2010; Danielsson et al., 2012; He and Krishnamurthy, 2012; Duffie and Strulovici, 2012; Brunnermeier and Sannikov, 2014; Adrian and Shin, 2014; Gertler and Kiyotaki, 2015.

[2] Broker-dealer book leverage is computed as the total financial assets aggregated across broker-dealers in the U.S. divided by their aggregated book equity.

obtained using in-sample and out-of-sample tests (Goyal and Welch, 2008; Campbell and Thompson, 2008) while controlling for data mining (Rapach and Wohar, 2006; Harvey et al., 2016). Compared to the popular forecasting variables, the bank asset factor is the only one that has positive and significant in-sample and out-of-sample $R^2$, both in recessions and expansions. The predictive power of asset growth does not depend on the 2007-2009 financial crisis. Bank assets are found to be an important predictor with high frequency data (weekly and monthly) which is a new finding compared to the existing literature on financial intermediaries. Indeed, performing monthly empirical tests with other intermediary asset pricing factors, such as the Adrian et al. (2014) and He et al. (2017) variables,[3] leads to mixed results.

Interestingly, we find that the predictive coefficients on the bank asset factor follow patterns across assets that are consistent with a risk-based explanation. The slopes from the forecasting regressions increase in magnitude from bonds to options to stocks, from high-grade to low-grade bonds, and from big and low book-to-market to small and high book-to-market stocks. This pattern is consistent with the business risks of the assets, and thus supports the risk-based explanation of our results.

We run cross-sectional asset pricing tests to examine whether the bank asset factor is priced. It is worth stressing that Adrian et al. (2014) and He et al. (2017) conduct asset pricing tests based on $R^2$s as well as on Shanken's (1992) *t*-statistics. However, the literature on empirical asset pricing tests has encouraged the use of higher hurdle than the use of the aforementioned criteria (Lewellen et al., 2010; Kan et al., 2014; Harvey et al, 2016). In particular, Kan et al. (2014) propose corrected *t*-statistics and develop formal statistical tests based on $R^2$s under the assumption of potentially misspecified models. When we apply these tests at a monthly frequency, we find that the risk premium on the He et al. (2017) factor is

[3] He et al. (2017) use the intermediary equity capital ratio of primary dealers

not statistically significant for all asset classes. By contrast, we document a negative and significant risk premium on the bank asset factor even in the cross-section of all assets.

Our paper makes two contributions to the literature on intermediary asset pricing. Adrian et al. (2014, 2015), He et al. (2017) and Baron and Muir (2018) do not implement out-of-sample and utility-based tests and do not deal with data mining. In addition, they do not examine predictability at monthly and weekly frequency. Second, in the cross-sectional asset pricing tests, the previous literature has not accounted for potential misspecification. More importantly, Baron and Muir (2018) who focus on the yearly asset growth of commercial banks do not implement asset pricing tests to show that the bank asset factor is priced which is important to support the risk-based explanation related to bank asset growth.

Our paper also makes a contribution to the literature on return predictability (Rapach and Wohar, 2006; Goyal and Welch, 2008; Campbell and Thompson, 2008; Rapach et al., 2010; Jordan et al., 2017; etc.). Harvey et al. (2016) have recently proposed different approaches to deal with data mining in the cross-section of equity returns. They argue that because researchers have investigated the pricing of hundreds of factors, this data mining requires the use of a tougher significance level than that used in the literature. To the best of our knowledge, our paper is the first to apply the approaches recommended by Harvey et al. (2016) to the forecasting exercise.

The rest of the paper is organized as follows. Section 2 describes the data on commercial banks' balance sheets. Section 3 presents the econometric methodology. Section 4 reports the empirical results regarding predictability. Section 5 presents the empirical results regarding cross-sectional asset pricing tests. Section 6 concludes.

# 2 Data

## 2.1 The data on commercial banks' balance sheets

We collected data on commercial banks' balance sheets from the Federal Reserve website,[4] which provides an estimated aggregate balance sheet using the weekly reports of a sample of domestically chartered commercial banks as well as U.S. branches and agencies of foreign banks. All data are in millions of dollars. The information is released weekly on Friday, and the monthly levels are the pro rata averages of weekly levels. Bank assets include securities, loans and leases, interbank loans, cash assets, and other assets. Commercial bank data on these items are available[5] from 1973 onwards, so the sample period examined in this paper is January 1973–December 2015.

The commercial bank data examined in this paper are different from those used by Adrian et al. (2015), who focus on the Consolidated Reports of Condition and Income (the quarterly Call Reports). The present paper instead uses the estimated monthly data reported in Table H8 (released by the Federal Reserve), which have been used by many papers such as Bernanke and Blinder (1992), Lown et al. (2000), Den Haan et al. (2007), and Acharya and Mora (2015). In the quarterly call reports, all federally insured banks are required to file income statement and balance sheet data to the Federal Deposit Insurance Corporation (FDIC), whereas the H8 data provide "an estimated weekly aggregate balance sheet for all commercial banks in the United States based on data that are reported weekly by a sample of approximately 875 domestically chartered banks and foreign-related institutions" (see notes on the release).[6] The H.8 series is based on weekly bank credit reports-form FR2644—submitted to the Federal Reserve.[7]

[4] H.8. Assets and Liabilities of Commercial Banks in the United States.
[5] https://www.federalreserve.gov/releases/h8/20151231/
[6] http://www.federalreserve.gov/releases/h8/about.htm
[7] https://www.federalreserve.gov/reportforms/forms/FR_264420171231_f.pdf

Using the H8 data has two advantages. First, data on call reports are quarterly, while the H8 data are monthly and weekly. Using higher frequency data enables us to better capture the price dynamics caused by deteriorating funding conditions. Second, the data on call reports are released about one month after the end of the quarter, while the H8 data are published each Friday. This difference makes our data more useful for forecasting purposes because it is timelier.

Despite the fact that they are sampled at different frequencies, Den Haan et al. (2005) find that the two datasets are similar when the quarterly aggregate H8 data are compared to the call report data. This result is not surprising since the file explaining the instructions for the preparation of form FR 2644[8] states that "The FR 2644 report is a shortened version of the quarterly reports… In general, definitions of items on the FR 2644 report correspond to item definitions on the Call Reports." The instruction file presents a table at the end of the document that indicates the item-by-item relationship between the FR 2644 report and the quarterly reports. For example, bank assets are shown in item 6 in the FR 2644 report, while it is shown by item 8 in the call reports, but the definition is the same.

## 2.2 Other data

The bank asset factor is compared with the predictors used in Goyal and Welch (2008) as well as with the intermediary pricing factors used in Adrian et al. (2014, 2015) and He et al. (2017). To keep the comparison as fair as possible, we collect the data from Goyal's and He's websites.[9] Goyal's website provides an updated dataset of all forecasting variables used in Goyal and Welch (2008), i.e., the log dividend-price ratio (*LOGDY*), log earnings-price ratio (*LOGEP*), stock variance (*SVAR*), book-to-market value ratio for the DJIA (*BM*), net equity

[8] https://www.federalreserve.gov/reportforms/forms/FR_264420171231_i.pdf
[9] http://www.hec.unil.ch/agoyal
http://apps.olin.wustl.edu/faculty/manela/hkm/intermediarycapitalrisk/He_Kelly_Manela_Factors.zip

expansion (*NTIS*), Treasury bill rate (*TBL*), term spread (*TMS*), default yield spread (*DFY*), and inflation (*INFL*). *LOGDP* is computed as the log of a 12-month moving sum of dividends accruing to the S&P 500 index minus the log of stock prices. Earnings are substituted for dividends in the computation of *LOGEP*. *SVAR* is the sum of squared daily returns on the S&P 500 index. *NTIS* is the net equity expansion ratio advocated by Baker and Wurgler (2000), which is the 12-month moving sum of net issues by NYSE-listed stocks divided by the market capitalization of NYSE stocks. *TMS* is the difference between the long-term yield and the three-month Treasury bill rate. *DFY* is the difference between BAA and AAA corporate bond yields. For more details on these variables, see Goyal and Welch (2008).

He's website provides data on the He et al. (2017) variables. He et al. (2017) propose the intermediary equity capital ratio of primary dealers which is the inverse of the Adrian et al. (2014) leverage variable. The difference between both variables is that He et al. (2017) rely on data at the holding company level for primary dealers, while Adrian et al. (2014) resort to the Flow of Funds data, which provide data information at the broker-dealer subsidiary level. While the data on the He et al. (2017) variable are available with monthly and quarterly frequency, the broker-dealer book leverage cannot be computed monthly, since it involves using quarterly data (Table L113 from the Federal Reserve website). For monthly tests, we compute the quarterly broker-dealer book leverage using the data from Table L113, then we transform the quarterly time-series by assigning each observation in the quarterly series to the last monthly observations corresponding to the quarterly period. Using this method ensures that there is no look-ahead bias for broker-dealer book leverage.

He's website also provides data on the asset portfolios used in He et al. (2017) that will be used as dependent variables. The authors rely on a wide range of asset portfolios used in the previous literature. They resort to the 25 size-book-to-market stock portfolios used in Fama and French (1993) (the sample period is 1973M1-2012M12). Regarding bonds, they combine ten government bond portfolios sorted by maturity with ten yield spread-sorted portfolios of corporate bonds constructed by Nozawa (2014) (the sample period is 1975M1-2011M12). For sovereign bonds, they turn to the six portfolios from Borri and Verdelhan (2012) (the sample period is 1995M1-2009M12). They also use 18 option portfolios constructed from the 54 Constantinides et al (2013) option portfolios sorted by moneyless and maturity (the sample period is 1986M4-2011M12). For credit default swaps (CDS) contracts, they construct 20 spread-sorted portfolios using individual name 5-year contracts (the sample period is 2001M2-2012M12). They combine the six currency portfolios used in Menkhoff et al. (2012) and those used in Lettau et al. (2014) to form twelve currency portfolios (the sample period is 1976M3-2009M12). The Menkhoff et al. (2012) portfolios are formed using momentum, while those of Lettau et al. (2014) are built on the interest rate differential. For commodities, they use the returns on 23 commodity portfolios collected from the Commodities Research Bureau (the sample period is 1986M9-2012M12). For more details, see He et al. (2017) and reference therein.

## 2.3 Descriptive statistics

Panel A of Table 1 presents descriptive statistics for the growth in bank asset (*BKASSET*), other intermediary pricing variables, and popular predictors of stock returns. We see that the autocorrelation of *BKASSET* is relatively low, which is a desirable characteristic since Kothari and Shanken (1997) and Stambaugh (1999) emphasize that the coefficients in the forecasting regressions are upward biased when the independent variable is highly persistent. In addition, we observe a weak correlation between *BKASSET* and popular predictors of stock returns, which indicates that it could explain some return variation left unexplained by other variables.

[Table 1 about here]

Figure 1 depicts the time-series variation in *BKASSET* as well as the market excess return. The market return is calculated as the value-weight return on all New York Stock Exchange (NYSE), American Stock Exchange (AMEX) and National Association of Securities Dealers Automated Quotation (NASDAQ) stocks, as is the standard in most research papers. The market excess returns are obtained from Kenneth French's online data library.[10] Large drops in the value of commercial banks' total assets are observed during recessions, but sometimes we also observe increases in bank assets in recessions. Likewise, negative and positive market excess returns occur during recessions. This common feature of the two variables reinforces the argument of using *BKASSET* as a forecaster of stock returns.

[Figure 1 about here]

### 2.4 Economic conditions across low and high values of intermediary variables

Our main conjecture is that investors require high risk premium in periods of low *BKASSET* because these are states of weaker economic conditions. Moreover, as the bank asset factor measures credit supply to the whole economy, not only to dealers, it will be more related to economic conditions than the other intermediary pricing variables. To investigate this conjecture, we split the sample period based on the median of *BKASSET*. The observations below (above) the median belong to periods of low (high) *BKASSET*. We collect data on nominal consumption, investment, and *GDP* from the Bureau of Economic Analysis, U.S. Department of Commerce. Consumption includes nondurables and services. Investment is computed as the sum of residential and non-residential investments. Only quarterly data are

[10] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

available for investment and *GDP*. The growth rate is computed as the log change in the level of each macroeconomic variable. Quarterly bank asset data are computed as the monthly average level of bank assets during a quarter.

[Table 2 about here]

The results reported in Table 2 backs up our prediction. Panel A of Table 2 shows clearly that the average growth in quarterly consumption, investment, and *GDP* is significantly lower in periods of low *BKASSET* than in periods of high *BKASSET,* which indicates that the former periods are characterized by higher economic uncertainty, thereby explaining the higher risk premium required by investors. We perform the same analysis with the leverage factor of Adrian et al. (2014) and the intermediary capital ratio of primary dealers of He et al. (2017). The results indicate no systematic pattern in macroeconomic variables across low and high values of the aforementioned variables. Panels E to H show that using monthly consumption does not change the main conclusion drawn from Table 2.

It is worth noting that Adrian et al. (2015) examine the relation between bank leverage and asset prices, but they do not find the former to be informative about the latter. In order to shed light on their conclusion, we also construct the bank leverage factor as the ratio of bank assets divided by bank net worth. We see that the bank leverage factor is not related to economic conditions, which might explain the results in Adrian et al. (2015).

# 3 Econometric methodology

## 3.1 In-sample regressions

To examine the asset price dynamics, we run the following univariate regression:

$$r_{m,t+1} = a_j + b_j X_{j,t} + \varepsilon_{j,t+1} \qquad j = 1...K \tag{1}$$

where $r_{m,t+1}$ is the monthly excess return on the market at time $t+1$, $X_{j,t}$ denotes the predicting variable $j$ at time $t$, and $\varepsilon_{j,t+1}$ is the error term of regression $j$. $K$ is the number of competing forecasting variables, which is equal to ten here (*BKASSET* plus the nine forecasting variables described in the previous section). As in Goyal and Santa-Clara (2003) and Goyal and Welch (2008), we compute critical values through a bootstrap experiment.[11] Formally, we impose the null of no predictability and assume a first-order autoregressive process for the predictive variable:

$$r_{m,t+1} = a_0 + \varepsilon_{t+1} \tag{2}$$

$$X_{j,t+1} = \phi_0 + \phi_1 X_{j,t} + v_{j,t+1} \qquad j = 1...K \tag{3}$$

We estimate the parameters of equations (2)–(3) by OLS and extract the innovation processes $\varepsilon_{t+1}$ and $v_{j,t+1}$ without imposing any cross-correlation structure. We then replicate the residuals by sampling with replacement and use the estimated parameter to generate 10,000 bootstrapped time series. For each replication, we perform the forecasting regression and compute the Newey-West $t$-statistic of $b_j$. The bootstrap $p$-value is calculated by comparing the actual $t$-statistics with the bootstrapped $t$-statistics.[12]

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[11] Goyal and Welch (2008) state that their "bootstrap procedure not only preserves the autocorrelation structure of the predictor variable, thereby being valid under the Stambaugh (1999) specification, but also preserves the cross-correlation structure of the two residuals." It is worth noting that we use the bootstrap experiment here because many of the variables used in the literature are persistent, not because of the properties of our predictor, which does not suffer from a Stambaugh bias given the low serial correlation in *BKASSET*.

[12] When we compute bootstrap $p$-values, we take the negative of the variables for which the theory predicts a negative forecasting coefficient (see Rapach and Wohar, 2006) so that the alternative hypothesis is a strict positive $b_j$. We keep the original sign when we report the forecasting coefficient as well as its $t$-statistics.

We control the effect of data mining by implementing the approaches recommended by Rapach and Wohar (2006) and Harvey et al. (2016). Data mining refers to the problem that arises when researchers consider a large number of potential forecasters but focus on the best results. As pointed out by Rapach and Wohar (2006) and Jordan et al. (2017), the literature on return predictability is subject to this problem as many variables appear to predict future returns. They tackle this issue by computing the data mining robust critical value proposed by Inoue and and Kilian (2004). Instead of computing the bootstrap $p$-value of each factor in isolation as described above, Inoue and Kilian (2004) examine the null hypothesis as $H_0$: $b_j$=0 for all $j$ and the alternative hypothesis as $H_1$: $b_j$>0 for some $j$. The suggested statistic to examine this hypothesis is $\max_{j\in\{1\ldots K\}} t_{b_j}$ where $t_{b_j}$ the Newey-West $t$-statistic associated with $b_j$. Inoue and Kilian (2004) recommend using bootstrap procedures to compute the data mining robust critical value. See the Appendix for more details on the computation of the aforementioned robust critical value.

Harvey et al. (2016) have recently proposed a different approach to deal with data mining in the cross-section of equity returns. We apply their approach to the forecasting exercise. Harvey et al. (2016) propose to compute the Holm (1979) adjusted $p$-values to account for the Family-wise Error Rate (FWER). "FWER measures the probability of even a single false discovery, regardless of the total number of tests. For instance, researchers might test 100 factors; FWER measures the probability of incorrectly identifying one or more factors to be significant." Here, the null hypotheses subject to investigation are that the $K$ predicting variables are not significant (one by one). The Holm adjustment is a sequential method whose purpose is adjusting p-values to avoid identifying one or more factors to be significant while they are not. See the Appendix for more details on the computation of the adjusted $p$-values.

## 3.2 Out-of-sample regressions

To evaluate the forecasting power of predictive variable *j*, Goyal and Welch (2008) advocate the use of the out-of-sample (OOS) $R^2$:

$$OOSR_j^2 = 1 - (MSFE_j / MSFE_a) \tag{4}$$

$$MSFE_j = (1/T)\sum_{t=1}^{T}(r_{mt} - \hat{r}_{mt,j})^2 \qquad\qquad MSFE_a = (1/T)\sum_{t=1}^{T}(r_{mt} - \hat{r}_{mt,a})^2$$

where $\hat{r}_{mt,j}$ and $\hat{r}_{mt,a}$ are the expected market excess return using the predictive variable and the historical average return, respectively, and *MSFE* stands for mean squared forecasting error. A positive $OOSR^2$ indicates that the forecasting variable *j* is more accurate in predicting market excess returns than the historical average return. To examine whether the differences in *MSFEs* are statistically significant, we implement the tests of Diebold and Mariano (1995) (*DM*) and Clark and West (2007) (*CW*). When two competing forecasting variables originate from non-nested models, the *DM* statistic is approximately normally distributed with zero mean and unit variance. Clark and McCracken (2001) demonstrate that for nested models, the *DM* statistic has a non-standard asymptotic distribution. Clark and West (2007) propose a modified *DM* *t*-statistic (CW-$t_j$) for nested models, which has a standard normal asymptotic distribution. The CW-$t_j$ has been widely used in the predictability literature (Jordan et al., 2017) since the standard approach is to compare the results of predictors with the historical average return, which is nested by any forecasting regression that includes a constant.

Investigating the economic significance of the result through an asset allocation experiment is another way of assessing the usefulness of forecasting variables (Campbell and Thompson, 2008). In this experiment, a risk-averse investor is assumed to maximize his expected utility gains by constructing portfolios using predictive variable *j* or the historical average return. Campbell and Thompson (2008) compute the parameter $\Delta_j$ which is the difference between the average utility gains obtained by trading based on the predictive variable $j$ and trading based on the historical average return. The annual difference in the utility function $\Delta_j$ can be interpreted as the cost that an investor is willing to pay in exchange for using the information content in the predictive variable.

Data mining is also a potential problem in out-of-sample tests. Inoue and Kilian (2004) argue that "to the extent that data mining is a potential concern, we should be equally skeptical of in-sample and out-of-sample tests of predictability when standard critical values are used." We address this issue by using the same approaches described in the previous section. Following Rapach and Wohar (2006) and Jordan et al. (2017), we implement the bootstrap procedure to compute the data mining robust critical value based on the CW-$t_j$ and the economic value measure $\Delta_j$. Following Harvey et al. (2016), we control for data mining using the Holm adjustment made to the $p$-values associated with the CW-$t_j$ of each factor $j$. For more details, see the Appendix.

### 3.3 Asset pricing tests under the assumption of potentially misspecified models

In order to examine the cross-sectional implications of intermediary asset pricing models, we resort to the two-pass methodology developed by Kan et al. (2014). Because all models are an approximation of reality, they all suffer from misspecification. Kan et al. (2014) derive the correct standard errors of the risk premia estimates under the assumption of potentially misspecified models. Based on these standard errors, they propose formal tests of the $R^2$=0 and $R^2$=1 hypotheses.

Formally, assume that expected excess returns on assets are linear in their betas

$$E(r) = B\theta \tag{5}$$

where $E(r)$ is an $N\times 1$ vector including expected excess returns on assets. $B=[1_N, \beta_J]$, where $\beta_J$ is the $N\times J$ matrix of betas on $J$ risk factors and $1_N$ is an $N\times 1$ vector of ones. $\theta=[\theta_0, \theta_J']'$ where $\theta_J$ is a $J\times 1$ vector of risk premia associated with the $J$ risk factors and $\theta_0$ is the zero-beta rate. Let $f_t$ be the $J\times 1$ vector of observations on risk factors at time $t$, and let $r_t$ be an $N\times 1$ vector containing the excess returns on assets at time $t$. We define the sample counterpart of some population measures of interest as follows:

$$\bar{r}=(1/T)\sum_{t=1}^{T} r_t, \qquad \bar{f}=(1/T)\sum_{t=1}^{T} f_t \tag{6}$$

$$\hat{V}_J=(1/T)\sum_{t=1}^{T}(r_t-\bar{r})(f_t-\bar{f})' \tag{7}$$

$V_J$ is the $N\times J$ matrix consisting of the covariances of asset excess returns with the $J$ risk factors. We denote the covariance matrix of the $J$ risk factors by $V_{ff}$ and define their sample counterpart such that

$$\hat{V}_{ff}=(1/T)\sum_{t=1}^{T}(f_t-\bar{f})(f_t-\bar{f})' \tag{8}$$

The two-pass methodology starts with the estimation of asset betas such that $\hat{B}=[1_N, \hat{\beta}_J]$ and $\hat{\beta}_J=\hat{V}_J\hat{V}_{ff}^{-1}$. In the second stage, we estimate $\theta$ in (5) by regressing the average excess returns on $\hat{B}$, which gives

$$\hat{\theta}=(\hat{B}'\hat{B})^{-1}\hat{B}'\bar{r} \tag{9}$$

Kan et al. (2014) derive what they call the "misspecification robust *t*-ratio," which is computed using $\hat{V}_{\theta\theta}$, the estimated covariance matrix of $\hat{\theta}$.

$$\hat{V}_{\theta\theta} = (1/T)\sum_{t=1}^{T} \hat{h}_t \hat{h}_t' \tag{10}$$

$$\hat{h}_t = (\hat{\theta}_t - \hat{\theta}) - (\hat{\psi}_t - \hat{\psi})\,\hat{g}_t + \hat{H}\,\hat{z}_t \hat{u}_t \tag{11}$$

$\hat{\theta}_t \equiv [\hat{\theta}_{0t}, \hat{\theta}_{Jt}']' = (\hat{B}'\hat{B})^{-1}\hat{B}' r_t$, $\hat{\psi}_t \equiv [\hat{\theta}_{0t}, (\hat{\theta}_{Jt} - f_t)']'$, $\hat{\psi} \equiv [\hat{\theta}_0, (\hat{\theta}_J - \bar{f})']'$, $\hat{g}_t = \hat{\theta}_J' \hat{V}_J^{-1}(f_t - \bar{f})$, $\hat{H} = (\hat{B}'\hat{B})^{-1}$, $\hat{z}_t = [0, (f_t - \bar{f})'\hat{V}_J^{-1}]'$, $\hat{u}_t = \hat{e}'(r_t - \bar{r})$ with $\hat{e} = \bar{r} - \hat{B}\hat{\theta}$

In addition, Kan et al. (2014) derive the asymptotic distribution of the sample cross-sectional $R^2$, which depends on the assumed population $R^2$. Under the null hypothesis $H_0 : R^2 = 0$ , they demonstrate that the $T\hat{R}^2$ statistic is the weighted sum of *N-J* independently and identically distributed (i.i.d.) random variables with a $\chi_1^2$ distribution. Under the null hypothesis $H_0 : R^2 = 1$, the $T(\hat{R}^2 - 1)$ statistic is the weighted sum of *N-J* i.i.d. random variables with a $\chi_1^2$ distribution (for more details see Kan et al., 2014).

# 4 Empirical results regarding the forecasting power of banks' assets

## 4.1 In-sample regressions

Table 3 reports the parameter estimates of univariate regression (1) for *BKASSET* and the variables used in Goyal and Welch (2008). Notice that *BKASSET* has the highest in-sample $R^2$ (*IS*-$R^2$), which is statistically significant at the 1% level. The *t*-statistic on *BKASSET* is the highest in magnitude and it is the only one that is greater than the data mining robust critical values. The Holm adjustment leads to the conclusion that only *BKASSET* significantly predicts market excess returns.

[Table 3 about here]

Table 3 also displays the results for the recession and expansion periods. Henkel et al. (2011) find that the forecasting power of many variables is higher in recessions than in expansions. Regarding *BKASSET*, the *IS-*$R^2$ as well as $b_j$ are significantly different from zero at the 1% level, both in recession and expansion periods. The Holm adjustment leads to the conclusion that the bank asset factor is the only significant variable in both economic states.

## 4.2 Out-of-sample regressions

To appraise the out-of-sample predictability, we have to select an initial estimation period and a forecasting evaluation period. As a trade-off between statistical power and the fact that our sample begins in January 1973, we set the initial forecasting evaluation period to January 1983 and use a recursive scheme thereafter.

[Table 4 about here]

Table 4 presents the out-of-sample performance of the different predictors used in Goyal and Welch (2008) as well as *BKASSET*. The results in Table 4 are consistent with the findings obtained in the in-sample regressions. In the full period, the bank asset factor is the only predictor that yields a positive *OOS*$R^2$ and has a significantly lower *MSFE* than that of the historical average return. Controlling for data mining, we see that the bank asset factor is the only significant factor when we use the Holm adjustment. In addition, the actual CW-*t* on

*BKASSET* is higher than the 1% data mining robust critical value. Although the economic value measure associated with *BKASSET* is positive and statistically significant at the 5% level, the Holm adjustment leads to the conclusion that no predictive variables generate significant $\Delta$. The results are similar in recessions with the exception that the Holm adjustment indicates that *BKASSET* as well as *LOGDY, LOGEP,* and *SVAR* generate significant $\Delta$. In expansion periods, only inflation has a higher *OOSR²* than that of *BKASSET*, and both variables have significantly lower *MSFEs* than that of the historical average return, even after accounting for data mining. However, as in the full period, there are no variables that generate significant $\Delta$ after applying the Holm adjustment, which substantiates the result of Henkel et al. (2011) that predictability is stronger in recessions than in expansions.

### 4.3. The forecasting power of other intermediary asset pricing factors

We examine the forecasting power of three other intermediary asset pricing factors: the broker-dealer book leverage of Adrian et al (2014), the He et al. (2017) intermediary capital factor, and the leverage of commercial banks as computed in Adrian et al. (2015).

[Table 5 about here]

Table 5 presents the results of the different tests described above. We see that none of the existing intermediary asset pricing factors possess significant forecasting power, regardless of the implemented predictive tests. Our results are different from those of Adrian et al (2014) and He et al. (2017) because they performed quarterly or yearly rather than monthly predictive regressions. As explained above, it is more interesting to examine higher frequency data so that we better capture the price dynamics caused by deteriorating funding conditions. Panel D presents the results of a one-month ahead multivariate predictive regression, including *BKASSET* and the three intermediary pricing factors. Including these variables in the forecasting regression does not reduce the predictive power of *BKASSET*, while the coefficients of the other factors are not statistically significant at conventional levels. We interpret this finding as evidence that *BKASSET* better captures the price dynamics caused by financial frictions and changing intermediaries' balance sheet conditions.

### 4.4 Forecasting other asset portfolios

Investigating whether *BKASSET* predicts the excess returns on other assets is an important robustness check. As dependent variables, we use the asset portfolios examined in He et al. (2017). We also present the results for the other intermediary pricing variables. Table 6 reports the results for the average return on all assets of an asset class, as is done in He et al. (2017).

[Table 6 about here]

Whether we implement in-sample or out-of-sample tests, the parameters associated with *BKASSET* are statistically significant at the 5% level for all asset portfolios, except for sovereign bond portfolios and the out-of-sample tests pertaining to commodity portfolios. The in-sample predictive coefficient on *BKASSET* is negative for all asset portfolios and has a pattern across assets that support risk-based theory. Indeed, we see that the *BKASSET* predictive coefficient increases in magnitude from low risky asset such as sovereign bonds (-0.079) and bonds (-0.315) to high risky assets such as commodities (-0.666), options (-1.111) and stocks (-1.375). Given all of these findings, it is not surprising that *BKASSET* significantly predicts the average excess returns on all asset portfolios. By contrast, *INTCAP* and *LECFAC* possess weak forecasting power for all portfolios. Indeed, the predictive coefficient as well as the *IS*-$R^2$ and *OOSR*$^2$ in the tests comprising all portfolios are not statistically significant at conventional levels.

[Table 7 about here]

In order to shed more light on the risk-based explanation of the forecasting power of *BKASSET*, we present the results of the univariate forecasting regressions for individual portfolios within each asset category. Panels A and B present the results for the five book-to-market and five stock portfolios, whose data are collected from French's website. The results show clearly that high book-to-market stocks have higher *BKASSET* exposure than low book-to-market stocks, which is consistent with the fact that they have higher average returns, indicating that it is a compensation for risk. Similar results are obtained for small stocks relative to big stocks. Panel C presents the results for bond portfolios. For ease of exposition, we form six portfolios from the original 20 bond portfolios. The first portfolio contains the 10 government portfolios. The five remaining are the 10 corporate bond portfolios sorted according to their yield. We see that the *BKASSET* predictive coefficient increases in magnitude from government bonds to corporate bonds and from low-yield to high-yield corporate bonds, a systematic pattern which is consistent with risk-based intuition. For the other asset categories (except currencies), portfolios are sorted according to their average returns. The results show that, in general, the *BKASSET* predictive coefficient increases in magnitude from assets that have low average returns to assets that have high average returns, even for asset categories for which the forecasting power of *BKASSET* is low. Currency portfolios are the only assets for which average returns are not in line with the *BKASSET* predictive coefficient, even though *BKASSET* predicts currency excess returns over time. The fact that the cross-section of currency excess returns is driven by differences in fundamentals between the U.S. and other countries may explain the lack of relationship between *BKASSET* exposure and average returns across currency portfolios.

### 4.5 Robustness checks

Looking at Figure 1, one might wonder about the extent to which our results are driven by the subprime crisis. We reexamine the in-sample and out-of-sample tests of stock return predictability by excluding the 2007–2009 financial crisis. The results are not reported to save space. The $IS\text{-}R^2$ drops from 2.70% to 1.40%, and the magnitude of the coefficient of *BKASSET* decreases from -1.215 to -0.967, but both remain statistically significant at the 1% level. By and large, we can conclude that the subprime crisis does not fully account for the effect of *BKASSET* on stock prices. Furthermore, we perform the predictability tests across the subperiods 1973-1987 and 1987-2015, which helps in examining the stability of our result but will also help in investigating the impact of the revisions made by the *FED* to the H8 series. According to the H8 release, the series received minor revisions for the 1973-87 period, so one way to appraise the effect of the revisions on the result is to re-run our empirical tests using only the aforementioned period or excluding it from the sample period. The results (not reported) show that the forecasting power of *BKASSET* is robust to the different subperiods.

### 4.6 Empirical results using quarterly and weekly excess returns

While our main tests are carried out with monthly data, it is interesting to examine the performance of *BKASSET* in the forecasting regressions using quarterly excess returns. These tests will help to compare *BKASSET* with the other intermediary pricing factors. The data on portfolio returns as well as the He et al. (2017) and Adrian et al. (2014) factors are obtained from He's website. The quarterly data on traditional forecasting variables are from Goyal's website. Quarterly bank asset data are computed as the monthly average level of bank assets during a quarter.

[Table 8 about here]

The dependent variable is the average excess returns across asset portfolios in each category. Table 8 shows that, using all assets, the bank asset factor has the most significant in-sample forecasting coefficient and *IS-$R^2$* among the three variables. The Adrian et al. (2014) leverage ratio also performs relatively well in in-sample regressions. The He et al. (2017) variable has the least forecasting power for asset excess returns, especially in terms of out-of-sample performances.

Finally, we examine whether *BKASSET* predicts market excess returns at the weekly frequency. Forecasting excess returns with high frequency data using variables other than past returns themselves has been understudied in the literature given the lack of data as well as the common belief that predictability does not exist in weekly and daily regressions (Cochrane, 2005). The fact that bank asset data are released weekly allows us to examine predictability with high frequency data, which is not possible with other intermediary pricing factors. Table 9 reports the results of in-sample and out-of-sample tests when the dependent variable is the one-week-ahead market excess return, whose data are collected from Kenneth French's website. We use only three predictors: *BKASSET*, *TBL*, and *TMS*. The data on these variables are collected from the Federal Reserve website. *TMS* is computed as the difference between a 10-year government bond yield and the three-month Treasury bill rate. We are not able to use the other predictors given the lack of weekly data.

[Table 9 about here]

The results in Table 9 show that the forecasting coefficient on *BKASSET* is negative and statistically significant at the 1% level, and the associated *t*-statistic is higher than the data mining robust critical values. The *IS*-$R^2$ and *OOS*-$R^2$ are also statistically significant at conventional levels. Note also that *BKASSET* significantly improves the *OOS*-$R^2$ of the combination forecasts. Based on the Holm adjustment, the bank asset variable is the only significant factor. Particularly interesting is the high annualized difference in the utility function Δ, which is higher than the 1% data mining robust critical value. These findings indicate that weekly predictability via *BKASSET* is of economic significance. By contrast, we see that the other predictors do not possess any forecasting power.

# 5 Empirical results regarding cross-sectional asset pricing tests

The pattern in the predictive *BKASSET* coefficients suggests that the bank asset factor is priced in the cross-section of expected asset returns. Baron and Muir (2018) focus only on the predictive power of *BKASSET* and do not implement asset pricing tests. It is important to run such tests to show that investors care about the risk associated with *BKASSET* and to compare it with the other intermediary asset pricing variables. As underlined earlier, we conduct asset pricing tests under the assumption of potentially misspecified models, as done by Kan et al. (2014). The standard errors of the risk premium estimates are given by equation (11).

[Table 10 about here]

Table 10 presents the results of the misspecified robust *t*-statistics as well as the $R^2$=0 and $R^2$=1 tests. As in He et al. (2017), we examine a two-factor model containing market excess returns and the factor describing intermediaries' balance sheet conditions (*BKASSET*, *INTCAP* or *LEVFAC).* Except for currency portfolios, the risk premium associated with

*INTCAP* and *LEVFAC* is not statistically significant at conventional levels for all asset portfolios after adjusting for potential misspecification. The He et al. (2017) model passes the $R^2$=0 test only for bond and option portfolios and passes the $R^2$=1 test for option, CDS, and commodities portfolios. The Adrian et al. (2014) model passes the $R^2$=0 test for bond, sovereign bonds option, and CDS portfolios and passes the $R^2$=1 test only for bonds, sovereign bonds, and commodities portfolios. Given these findings, it is not surprising that *INTCAP* and *LEVFAC* do not have a significant premium in the cross-section containing all assets.[13] Overall, there is weak evidence that *INTCAP* and *LEVFAC* price all assets.

By contrast, the two-factor model comprising *BKASSET* does a better job in explaining the expected returns. The risk premium associated with *BKASSET* is statistically significant, at least at the 10% level for stocks, options, CDS, commodities, and currencies portfolios. Furthermore, in the cross-section of equity returns, the bank asset factor has a *t*-statistic greater than three, meeting the recommendation of Harvey et al. (2016). Our model passes the $R^2$=0 test at the 5% level for all portfolios, except commodities, for which we have to retain a 10% level to reject the zero-$R^2$ null hypothesis. Moreover, it passes the $R^2$=1 test at the 5% level for all asset portfolios, except for currency and options. These outcomes lead to better results for *BKASSET* in the cross-section of all assets' expected returns. We find that the associated risk premium is significantly different from zero at the 10% level, even after accounting for potential misspecification, and that the model including *BKASSET* passes the $R^2$=1 test at conventional levels. The fact that we are not able to reject the zero-$R^2$ null hypothesis appears to be at odds with the results of the $R^2$=1 test. The low number of time-series observations in the tests, including all portfolios, might explain this result, so it is more appropriate to emphasize the tests using each asset class separately.

[13] Because computing the standard errors of the risk premium estimates (equation (11)) requires that the time series of asset portfolios contain the same number of observations, the result in the last column of Table 10 differs from those reported in the last column of Table 11 in the He et al. (2017) paper.

It is worth noting that all intermediary asset pricing models yield consistent estimates of the zero-beta rate (the intercept of the cross-section), which reflects the difference between divergent lending and borrowing rates (Lewellen et al., 2010). Indeed, the zero-beta rate in both models is not statistically significant at the 5% level when using the misspecification *t*-statistic on the intercept. Regarding the market risk premium, the estimates in all models are sometimes negative, but not statistically significant.

Our interpretation of the sign of the risk premia is in the spirit of Maio and Santa-Clara (2012), who demonstrate that a state variable that predicts negative (positive) changes in investment opportunities should be associated with a negative (positive) risk premium in the cross-section of asset returns. The rationale is that the assets that do not covary with a state variable (zero betas) help investors hedge against adverse shocks to investment opportunities, thereby yielding zero risk premia. By contrast, assets with negative (positive) betas are more exposed to changes in investment opportunities, requiring high expected returns to compensate investors for holding them. The higher expected returns cannot happen only if the risk premium is negative (positive) so that expected returns are higher.

We do not report the betas on *BKASSET* to save space. The betas are generally negative, with a higher magnitude for assets with higher average excess returns. These patterns explain why the risk premia in Table 10 are negative for stocks, sovereign bonds, and options. The results are also plausible for corporate bonds, as the betas of high-yield corporate bonds are higher (in magnitude) than those of low-yield corporate bonds. However, the relationship between *BKASSET* betas and average excess returns is flat for government bonds, which explains why the risk premium for all bond portfolios is not statistically significant. The positive risk premium related to currency portfolios is explained by the fact that the average excess returns are negative, and since betas are negative, the risk premium is then positive. The positive risk premium associated with the CDS portfolios is driven by the last option portfolio, which has a low beta but high average excess return. When the last portfolio is removed from the cross-section, we find that the risk premium is not statistically significant.

[Table 11 about here]

Table 11 presents the results of the model combining market excess returns, *BKASSET* and other risk factors in the cross-section of expected asset returns. The results show that the risk premium associated with *BKASSET* is statistically significant at the 5% level in all models, which indicates that the effects of commercial banks on asset prices are not captured by other risk factors.

# 6 Conclusion

The empirical results in this paper reveal that *BKASSET* strongly predicts the excess returns on stocks, bonds, options, CDS, and currencies portfolios, even after controlling for data mining. In terms of forecasting power, the bank asset factor outperforms the intermediary capital factor of He et al. (2017) and the broker-dealer leverage factor of Adrian et al. (2014). Moreover, the bank asset factor possesses strong explanatory power for the cross-section of expected asset returns, even after accounting for potential misspecification. Finally, we document patterns across assets in the in-sample predictive coefficients on *BKASSET* that are consistent with risk-based theory. In general, we find that the *BKASSET* exposures increase in magnitude from low to high risky assets.

The bank asset factor has two advantages over the existing intermediary pricing factors. First, commercial banks' total assets are a more appropriate measure of funding liquidity than broker-dealer book leverage because it is a direct measure of credit supply to the whole economy, not only to dealers. Second, the bank asset data used here are released weekly by the Federal Reserve, which makes it more convenient than the existing intermediary pricing factor to capture the short-term price dynamics caused by financial frictions and changing financial intermediaries' balance sheet conditions.

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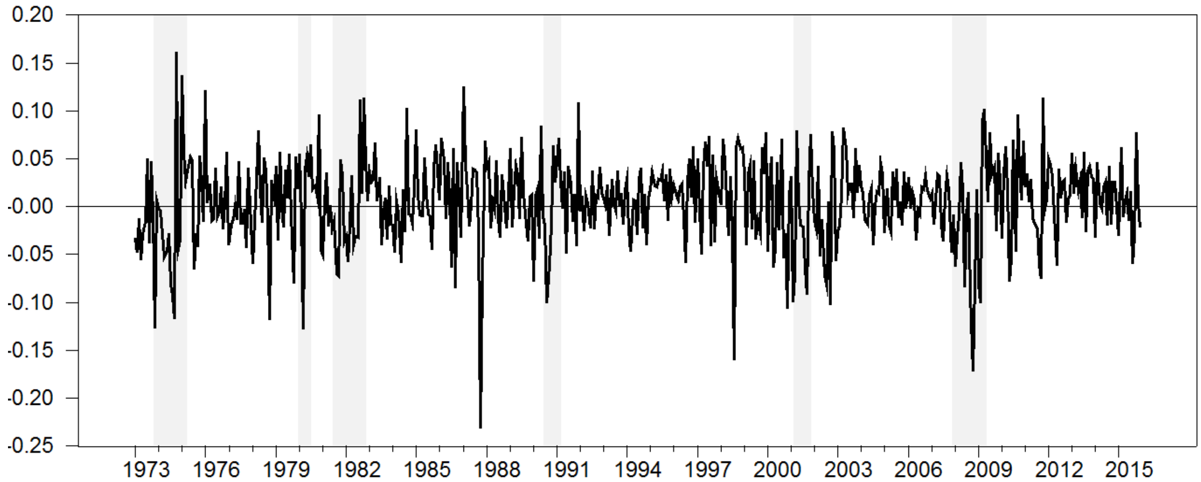
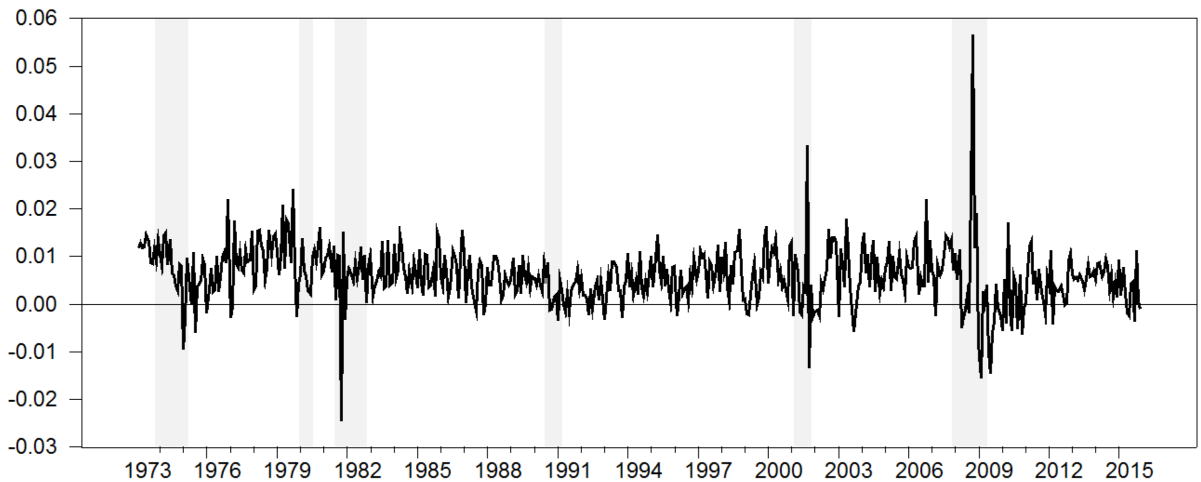
## Figure 1: Market Excess Return and *BKASSET*

Panel A: Market excess return




Panel B: *BKASSET*




Notes: This figure depicts the time-series variation in market excess return in Panel A and *BKASSET* in Panel B. Shaded areas indicate NBER recession periods. The sample period is January 1973–December 2015.

## Table 1: Descriptive Statistics

| Series | Mean | S.E | Min | Max | AC1 | *MKT* | *BKASSET* | *LEVFAC* | *INTCAP* | *LOGDY* | *LOGEP* | *SVAR* | *BM* | *NTIS* | *TBL* | *TMS* | *DFY* | *INFL* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | Correlation matrix | | | | | | | | | | | | |
| *MKT* | 0.01 | 0.01 | -0.02 | 0.06 | 0.24 | 1,00 | | | | | | | | | | | | |
| *BKASSET* | 0.01 | 0.05 | -0.23 | 0.16 | 0.07 | **-0,12** | 1.00 | | | | | | | | | | | |
| *LEVFAC* | 0.02 | 0.16 | -1.01 | 0.62 | 0.62 | 0,02 | **0.20** | 1.00 | | | | | | | | | | |
| *INTCAP* | 0.00 | 0.07 | -0.28 | 0.40 | 0.09 | **0,76** | **-0.14** | -0.01 | 1.00 | | | | | | | | | |
| *LOGDY* | -3.62 | 0.44 | -4.53 | -2.75 | 0.99 | 0,05 | 0.07 | 0.01 | -0.02 | 1.00 | | | | | | | | |
| *LOGEP* | -2.82 | 0.49 | -4.84 | -1.90 | 0.99 | -0,05 | **0.21** | **0.20** | **-0.15** | **0.73** | 1.00 | | | | | | | |
| *SVAR* | 0.00 | 0.00 | 0.00 | 0.07 | 0.46 | **-0,33** | **0.23** | 0.03 | **-0.26** | -0.08 | **-0.20** | 1.00 | | | | | | |
| *BM* | 0.49 | 0.29 | 0.12 | 1.21 | 0.99 | -0,05 | **0.15** | 0.03 | **-0.11** | **0.90** | **0.82** | -0.08 | 1.00 | | | | | |
| *NTIS* | 0.01 | 0.02 | -0.06 | 0.05 | 0.98 | -0,02 | 0.00 | -0.05 | 0.01 | 0.04 | **0.10** | **-0.22** | **0.13** | 1.00 | | | | |
| *TBL* | 0.05 | 0.03 | 0.00 | 0.16 | 0.99 | -0,07 | **0.17** | 0.07 | -0.06 | **0.66** | **0.68** | **-0.15** | **0.69** | 0.09 | 1.00 | | | |
| *TMS* | 0.07 | 0.03 | 0.02 | 0.14 | 0.99 | -0,03 | 0.08 | 0.08 | -0.04 | **0.76** | **0.62** | **-0.13** | **0.71** | **0.14** | **0.87** | 1.00 | | |
| *DFY* | 0.01 | 0.00 | 0.01 | 0.03 | 0.96 | 0,04 | -0.06 | **-0.16** | 0.03 | **0.47** | **0.11** | **0.28** | **0.45** | **-0.32** | **0.21** | **0.34** | 1.00 | |
| *INFL* | 0.00 | 0.00 | -0.02 | 0.02 | 0.64 | **-0,11** | 0.06 | -0.08 | **-0.09** | **0.43** | **0.50** | **-0.23** | **0.55** | **0.17** | **0.49** | **0.35** | -0.02 | 1.00 |

Notes: This table reports descriptive statistics for the variables used in the empirical tests. *BKASSET* is the growth in bank assets, *INTCAP* the intermediary capital factor, *LEVFAC* the broker-dealer leverage factor, *LOGDY* log dividend yield, *LOGEP* log earnings-price ratio, *SVAR* stock variance, *BM* book-to-market value ratio for the DJIA, *NTIS* net equity expansion, *TBL* Treasury bill rate, *TMS* term spread, *DFY* default yield spread, and *INFL* inflation. The sample period is January 1973–December 2015. "ac1" stands for first-order autocorrelation.

## Table 2: Consumption, Investment, and *GDP* across Low and High Values of Intermediary Variables

| Panel A: Quarterly consumption, investment, and *GDP* in low and high *BKASSET* | | | | |
|---|---|---|---|---|
| | High *BKASSET* | Low *BKASSET* | Difference | *t*-difference |
| Consumption growth | 1.628 | 1.114 | 0.514 | 3.406 |
| Invetsment growth | 1.995 | 0.952 | 1.043 | 2.399 |
| GDP growth | 1.763 | 1.249 | 0.514 | 2.932 |
| **Panel B: Quarterly consumption, investment, and *GDP* in low and high *LEVFAC*** | | | | |
| | High *LEVFAC* | Low *LEVFAC* | Difference | *t*-difference |
| Consumption growth | 1.343 | 1.326 | 0.016 | 0.106 |
| Invetsment growth | 1.730 | 1.223 | 0.507 | 1.233 |
| GDP growth | 1.514 | 1.441 | 0.073 | 0.440 |
| **Panel C: Quarterly consumption, investment, and *GDP* in low and high *INTCAP*** | | | | |
| | High *INTCAP* | Low *INTCAP* | Difference | *t*-difference |
| Consumption growth | 1.375 | 1.293 | 0.082 | 0.557 |
| Invetsment growth | 1.571 | 1.379 | 0.193 | 0.488 |
| GDP growth | 1.538 | 1.422 | 0.116 | 0.707 |
| **Panel D: Quarterly consumption, investment, and *GDP* in low and high *BKLEV*** | | | | |
| | High *BKLEV* | Low *BKLEV* | Difference | *t*-difference |
| Consumption growth | 1.375 | 1.376 | -0.001 | -0.007 |
| Invetsment growth | 1.634 | 1.335 | 0.298 | 0.686 |
| GDP growth | 1.554 | 1.476 | 0.078 | 0.431 |
| **Panel E: Monthly consumption in low and high *BKASSET*** | | | | |
| | High *BKASSET* | Low *BKASSET* | Difference | *t*-difference |
| Consumption growth | 0.525 | 0.391 | 0.134 | 3.421 |
| **Panel F: Monthly consumption in low and high *LEVFAC*** | | | | |
| | High *LEVFAC* | Low *LEVFAC* | Difference | *t*-difference |
| Consumption growth | 0.426 | 0.463 | -0.036 | -0.954 |
| **Panel G: Monthly consumption in low and high *INTCAP*** | | | | |
| | High *INTCAP* | Low *INTCAP* | Difference | *t*-difference |
| Consumption growth | 0.434 | 0.481 | -0.047 | -1.229 |
| **Panel H: Monthly consumption in low and high *BKLEV*** | | | | |
| | High *BKLEV* | Low *BKLEV* | Difference | *t*-difference |
| Consumption growth | 0.470 | 0.446 | 0.025 | 0.637 |

Notes: This table presents the average growth in consumption, investment, and *GDP* across periods of low and high values of intermediary variables. Variables are defined in Table 1. *BKLEV* is the bank leverage as used in Adrian et al. (2015). The observations below (above) the median of an intermediary pricing variable belong to periods of low (high) values. The last two columns report the average difference across the two sub-periods and the associated *t*-statistics (*t*-difference) which are corrected for heteroskedasticity and autocorrelation using the Newey-West estimator. Consumption includes nondurables and services. Investment is computed as the sum of residential and non-residential investments. Quarterly bank asset data are computed as the monthly average level of bank assets during a quarter. The sample period runs from 1973 to 2015.

Table 3: A Comparison between *BKASSET* and Popular Predictors: In-Sample Tests

| Variable | Overall | | Recession | | Expansion | |
|---|---|---|---|---|---|---|
| | *b* | *IS-R²* | *b* | *IS-R²* | *b* | *IS-R²* |
| *BKASSET* | | | | | | |
| estimate | -1.215 | 0.027 | -1.775 | 0.074 | -0.856 | 0.012 |
| *t*-statistic | -3.803 | | -3.595 | | -2.379 | |
| *p*-value | **0.000** | **0.000** | **0.000** | **0.000** | **0.005** | 0.008 |
| *LOGDY* | | | | | | |
| estimate | 0.005 | 0.003 | 0.028 | 0.042 | 0.004 | 0.002 |
| *t*-statistic | 1.110 | | 1.979 | | 0.918 | |
| *p*-value | 0.155 | 0.265 | 0.025 | **0.000** | 0.180 | 0.348 |
| *LOGEP* | | | | | | |
| estimate | 0.002 | 0.001 | 0.004 | 0.002 | 0.003 | 0.001 |
| *t*-statistic | 0.426 | | 0.304 | | 0.655 | |
| *p*-value | 0.501 | 0.602 | 0.499 | 0.318 | 0.468 | 0.497 |
| *SVAR* | | | | | | |
| estimate | -0.989 | 0.011 | -0.728 | 0.008 | -0.794 | 0.001 |
| *t*-statistic | -2.304 | | -0.863 | | -1.932 | |
| *p*-value | 0.040 | 0.014 | 0.215 | 0.031 | 0.083 | 0.497 |
| *BM* | | | | | | |
| estimate | 0.002 | 0.000 | 0.002 | 0.000 | 0.002 | 0.000 |
| *t*-statistic | 0.258 | | 0.258 | | 0.258 | |
| *p*-value | 0.696 | 0.828 | 0.707 | 0.831 | 0.651 | 0.813 |
| *NTIS* | | | | | | |
| estimate | -0.038 | 0.000 | 0.144 | 0.003 | -0.201 | 0.008 |
| *t*-statistic | -0.272 | | 0.391 | | -2.309 | |
| *p*-value | 0.385 | 0.694 | 0.405 | 0.257 | 0.986 | 0.042 |
| *TBL* | | | | | | |
| estimate | -0.073 | 0.003 | 0.034 | 0.001 | -0.060 | 0.002 |
| *t*-statistic | -1.254 | | 0.196 | | -1.162 | |
| *p*-value | 0.098 | 0.222 | 0.326 | 0.623 | 0.862 | 0.290 |
| *TMS* | | | | | | |
| estimate | -0.043 | 0.001 | 0.205 | 0.009 | -0.062 | 0.001 |
| *t*-statistic | -0.525 | | 0.820 | | -0.855 | |
| *p*-value | 0.759 | 0.606 | 0.291 | 0.038 | 0.851 | 0.401 |
| *DFY* | | | | | | |
| estimate | 0.530 | 0.003 | 2.061 | 0.050 | 0.577 | 0.002 |
| *t*-statistic | 0.835 | | 1.663 | | 1.149 | |
| *p*-value | 0.239 | 0.238 | 0.051 | **0.000** | 0.128 | 0.251 |
| *INFL* | | | | | | |
| estimate | -0.843 | 0.004 | 0.210 | 0.000 | -0.956 | 0.004 |
| *t*-statistic | -1.234 | | 0.155 | | -1.623 | |
| *p*-value | 0.112 | 0.166 | 0.442 | 0.705 | 0.951 | 0.117 |

Notes: This table presents the results of univariate predictive monthly regression (1). The dependent variable is the monthly market excess return. The independent variables are *BKASSET* and the forecasting variables used in Goyal and Welch (2008). These variables are defined in Table 1. *b* is the coefficient on the forecasting variable and below are the associated *t*-statistics corrected for heteroskedasticity and autocorrelation using the Newey-West estimator with four lags. *IS-R²* is the in-sample $R^2$ of the predictive regression. *P*-values are computed using bootstrap simulations. Values in bold type indicate significance using the Holm adjustment. The data mining robust critical values for the *t*-statistic are 2.659 (10%), 2.963 (5%), and 3.622 (1%). The results are presented for the full sample period January 1973–December 2015 (516 observations) as well as for the NBER recession and expansion periods (77 and 439 observations, respectively).

## Table 4: A Comparison between *BKASSET* and Popular Predictors: Out-Of-Sample Performance

| Variable | Overall | | Recession | | Expansion | |
|---|---|---|---|---|---|---|
| | *OOS-R²* | Δ | *OOS-R²* | Δ | *OOS-R²* | Δ |
| *BKASSET* | | | | | | |
| estimate | 0.017 | 1.271 | 0.061 | 2.467 | 0.005 | 1.125 |
| *t*-statistic | 2.257 | | 1.339 | | 1.899 | |
| *p*-value | **0.000** | 0.049 | **0.004** | **0.007** | **0.000** | 0.071 |
| *DY* | | | | | | |
| estimate | -0.027 | -0.400 | 0.026 | 8.544 | -0.041 | -1.320 |
| *t*-statistic | -0.477 | | 1.637 | | -0.874 | |
| *p*-value | 0.492 | 0.643 | **0.001** | **0.000** | 0.725 | 0.942 |
| *EP* | | | | | | |
| estimate | -0.027 | 0.724 | -0.008 | 10.096 | -0.032 | -0.232 |
| *t*-statistic | -1.202 | | 0.038 | | -1.573 | |
| *p*-value | 0.849 | 0.191 | 0.225 | **0.000** | 0.965 | 0.553 |
| *SVAR* | | | | | | |
| estimate | -0.065 | -0.110 | 0.031 | 4.024 | -0.091 | -0.530 |
| *t*-statistic | -0.538 | | 0.926 | | -1.007 | |
| *p*-value | 0.529 | 0.540 | 0.023 | **0.000** | 0.770 | 0.901 |
| *BM* | | | | | | |
| estimate | -0.037 | -0.456 | 0.001 | 2.686 | -0.047 | -0.777 |
| *t*-statistic | -1.490 | | 0.254 | | -1.560 | |
| *p*-value | 0.927 | 0.655 | 0.139 | 0.033 | 0.960 | 0.770 |
| *NTIS* | | | | | | |
| estimate | -0.011 | -0.734 | -0.046 | -12.257 | -0.001 | 0.461 |
| *t*-statistic | 1.238 | | -1.958 | | 1.900 | |
| *p*-value | 0.010 | 0.830 | 0.984 | 1.000 | **0.000** | 0.228 |
| *TBL* | | | | | | |
| estimate | -0.002 | -0.526 | -0.023 | -12.023 | 0.004 | 0.667 |
| *t*-statistic | 0.617 | | -1.536 | | 1.310 | |
| *p*-value | 0.060 | 0.686 | 0.933 | 1.000 | **0.003** | 0.187 |
| *TMS* | | | | | | |
| estimate | -0.004 | -0.831 | -0.004 | -0.990 | -0.004 | -0.809 |
| *t*-statistic | -1.066 | | -0.535 | | -0.920 | |
| *p*-value | 0.794 | 0.828 | 0.531 | 0.859 | 0.728 | 0.800 |
| *DFY* | | | | | | |
| estimate | -0.020 | -0.556 | -0.020 | -5.521 | -0.020 | -0.067 |
| *t*-statistic | -0.527 | | -0.533 | | -0.287 | |
| *p*-value | 0.516 | 0.775 | 0.526 | 1.000 | 0.392 | 0.455 |
| *INFL* | | | | | | |
| estimate | 0.001 | -0.291 | -0.038 | -9.502 | 0.012 | 0.651 |
| *t*-statistic | 1.084 | | -1.125 | | 2.206 | |
| *p*-value | 0.017 | 0.611 | 0.827 | 1.000 | **0.000** | 0.133 |

Notes: This table presents the out-of-sample forecasting performance of *BKASSET* as well as the predictive variables defined in Table 1. The dependent variable is the monthly market excess return. *OOS-R²* is the out-of-sample $R^2$ proposed by Goyal and Welch (2008). The table also presents the *t*-statistic corresponding to Clark and West's (2007) test. Δ is the annualized difference between the average utility gains obtained by trading on the basis of the predictive variable and trading on the historical average return. *P*-values are computed using bootstrap simulations. Values in bold type indicate significance using the Holm adjustment. The data mining robust critical values for the CW-*t* are 0.466 (10%), 0.732 (5%), and 1.235 (1%). The data mining robust critical values for Δ are 2.911 (10%), 3.512 (5%), and 4.740 (1%). The results are presented for the period January 1983–December 2015 (396 observations) as well as for the NBER recession and expansion periods (36 and 360 observations, respectively). The initial estimation period is January 1973–December 1982 (120 observations).

Table 5: Predicting Market Excess Returns using other Intermediary Pricing Variables

| | *b* | *IS-R²* | *OOS-R²* | Δ |
|---|---|---|---|---|
| | | Panel A: *INTCAP* | | |
| estimate | 0.000 | 0.005 | -0.021 | 0.376 |
| *t*-statistic | 1.319 | | -0.380 | |
| *p*-value | 0.174 | 0.118 | 0.415 | 0.295 |
| | | Panel B: *LEVFAC* | | |
| estimate | 0.001 | 0.000 | -0.015 | -0.866 |
| *t*-statistic | 0.052 | | -0.927 | |
| *p*-value | 0.527 | 0.961 | 0.291 | 0.841 |
| | | Panel C: *BKLEV* | | |
| estimate | 0.001 | 0.002 | -0.001 | -1.224 |
| *t*-statistic | 0.835 | | 0.489 | |
| *p*-value | 0.790 | 0.405 | 0.090 | 0.920 |

Panel D: Predictive regression with *BKASSET* and intermediary pricing variables

| | *CST* | *BKASSET* | *INTCAP* | *LEVFAC* | *BKLEV* |
|---|---|---|---|---|---|
| Coef | 0.008 | -1.322 | 0.000 | 0.016 | 0.008 |
| *t*-stat | 1.822 | -3.703 | 1.551 | 0.970 | 0.142 |
| *IS-R²* | 0.036 | | | | |

Notes: This table presents the results of in-sample and out-of-sample tests when we use different intermediary pricing variables. The dependent variable is the monthly market excess return. Panel A reports the results of the predictive regression when we use the He et al. (2017) intermediary capital factor. Panel B reports the results of the predictive regression when we use the leverage factor of Adrian et al (2014). Panel C reports the results of the predictive regression when we use the leverage of commercial banks. *BKLEV* is computed as in Adrian et al (2015). Panel D presents the results of the predictive multivariate regression including *BKASSET* and the three aforementioned intermediary pricing variables. The statistics are defined in Tables 3-4. For in-sample tests, the sample period is January 1973–December 2015. For out-of-sample tests, the sample period is January 1983–December 2015. The initial estimation period is January 1973–December 1982.

## Table 6: Predicting other Asset Portfolios: Comparison with the Intermediary Pricing Variables

| | 25 FF | | | 20 US Bonds | | | 6 Sov. Bonds | | | 18 Options | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *BKASSET* | *LEVFAC* | *INTCAP* | *BKASSET* | *LEVFAC* | *INTCAP* | *BKASSET* | *LEVFAC* | *INTCAP* | *BKASSET* | *LEVFAC* | *INTCAP* |
| *b* | -1.375 | 0.001 | 0.000 | -0.315 | -0.001 | 0.000 | -0.079 | -0.026 | 0.000 | -1.111 | -0.002 | 0.000 |
| *p*-value | **0.000** | 0.681 | 0.136 | 0.017 | -0.132 | 0.369 | 0.401 | 0.061 | 0.047 | **0.002** | 0.417 | 0.236 |
| *IS-R²* | 0.028 | 0.000 | 0.006 | 0.025 | 0.000 | 0.002 | 0.000 | 0.024 | 0.016 | 0.028 | 0.000 | 0.007 |
| *p*-value | **0.000** | 0.454 | 0.108 | **0.000** | 0.862 | 0.354 | 0.796 | 0.041 | 0.094 | **0.000** | 0.847 | 0.151 |
| *OOS-R²* | 0.021 | -0.021 | -0.018 | -0.009 | -0.108 | -0.048 | -0.082 | -0.049 | -0.136 | 0.010 | -0.029 | -0.027 |
| *p*-value | **0.000** | 0.555 | 0.220 | 0.012 | 0.010 | 0.810 | 0.701 | 0.485 | 0.430 | 0.028 | 0.999 | 0.875 |
| Months | 480 | | | 444 | | | 180 | | | 309 | | |

| | 20 CDS | | | 23 Commodities | | | 12 FX | | | ALL | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *BKASSET* | *LEVFAC* | *INTCAP* | *BKASSET* | *LEVFAC* | *INTCAP* | *BKASSET* | *LEVFAC* | *INTCAP* | *BKASSET* | *LEVFAC* | *INTCAP* |
| *b* | -0.221 | -0.010 | 0.000 | -0.666 | -0.019 | 0.000 | -0.395 | -0.006 | -0.000 | -0.814 | 0.003 | 0.000 |
| *p*-value | 0.008 | 0.010 | 0.101 | 0.047 | 0.147 | 0.628 | 0.006 | 0.270 | 0.969 | **0.000** | 0.575 | 0.161 |
| *IS-R²* | 0.095 | 0.121 | 0.038 | 0.016 | 0.009 | 0.000 | 0.014 | 0.002 | 0.019 | 0.037 | 0.000 | 0.005 |
| *p*-value | **0.000** | **0.001** | 0.024 | 0.024 | 0.089 | 0.773 | 0.019 | 0.363 | 0.004 | **0.000** | 0.677 | 0.142 |
| *OOS-R²* | 0.078 | 0.076 | -0.161 | -0.010 | -0.005 | -0.015 | 0.009 | -0.017 | -0.001 | 0.019 | -0.044 | -0.025 |
| *p*-value | 0.047 | 0.010 | 0.820 | 0.801 | 0.850 | 0.780 | **0.000** | 0.260 | **0.000** | **0.000** | 0.165 | 0.170 |
| Months | 143 | | | 316 | | | 406 | | | 480 | | |

Notes: This table presents the results of in-sample and out-of-sample tests when we use as dependent variable the average monthly excess return on all assets of an asset class. The predictive variables are *BKASSET*, *INTCAP*, and *LEVFAC*. The statistics are defined in Tables 3-4. 25 FF indicates the 25 size-book-to-market stock portfolios used in Fama and French (1993). 20 US Bonds indicate a combination of ten government bond portfolios and the ten corporate bond portfolios constructed by Nozawa (2014). 6 Sov. Bonds indicate the sovereign bond portfolios used in Borri and Verdelhan (2012). 18 Options are the option portfolios constructed by He et al. (2017). 20 CDS indicate 20 spreads-sorted portfolios using individual name 5-year contracts. 23 Commodities indicate 23 commodity portfolios constructed from the Commodities Research Bureau. 12 FX indicates a combination of the six currency portfolios used in Menkhoff et al. (2012) and those used in Lettau et al. (2014). All means all asset classes. The dataset is an unbalanced panel of returns. Months indicate the number of monthly observations in the in-sample tests. For out-of-sample tests, the initial estimation period contains five years of monthly returns (60 observations).

## Table 7: Predicting Individual Portfolios

| | | | | | | |
|---|---|---|---|---|---|---|
| Panel A: Book-to-market | | | | | | |
| | Lo Bm | 2 | 3 | 4 | Hi Bm | |
| Mean Return | 0.440 | 0.624 | 0.632 | 0.626 | 0.873 | |
| *b* | -1.097 | -1.193 | -1.300 | -1.521 | -1.687 | |
| *t*-statistic | -3.414 | -3.933 | -4.421 | -3.625 | -3.609 | |
| Panel B: Size | | | | | | |
| | Lo Size | 2 | 3 | 4 | Hi Size | |
| Mean Return | 0.692 | 0.716 | 0.708 | 0.676 | 0.481 | |
| *b* | -1.279 | -1.299 | -1.204 | -1.303 | -1.191 | |
| *t*-statistic | -2.529 | -2.871 | -2.909 | -3.465 | -4.025 | |
| Panel C: Bonds | | | | | | |
| | Gov. | Corp Lo yield | 2 | 3 | 4 | Corp Hi yield |
| Mean Return | 0.141 | 0.181 | 0.225 | 0.262 | 0.295 | 0.435 |
| *b* | -0.147 | -0.412 | -0.391 | -0.502 | -0.588 | -0.790 |
| *t*-statistic | -1.271 | -1.873 | -1.729 | -2.604 | -3.193 | -4.379 |
| Panel D: Sovereign Bonds | | | | | | |
| | Lo ret | 2 | 3 | 4 | 5 | Hi ret |
| Mean Return | 0.212 | 0.382 | 0.615 | 0.613 | 0.889 | 1.223 |
| *b* | 0.217 | 0.002 | -0.019 | -0.087 | -0.328 | -0.664 |
| *t*-statistic | 0.778 | 0.007 | -0.053 | -0.276 | -1.019 | -1.104 |
| Panel E: Options | | | | | | |
| | Lo ret | 2 | 3 | 4 | 5 | Hi ret |
| Mean Return | -0.190 | -0.042 | 0.140 | 0.450 | 0.695 | 1.180 |
| *b* | -0.547 | -0.784 | -0.933 | -1.299 | -1.461 | -1.599 |
| *t*-statistic | -1.514 | -2.161 | -2.521 | -2.735 | -2.825 | -2.863 |
| Panel F: CDS | | | | | | |
| | Lo ret | 2 | 3 | 4 | Hi ret | |
| Mean Return | -0.042 | -0.016 | -0.010 | 0.022 | 0.262 | |
| *b* | -0.066 | -0.087 | -0.171 | -0.242 | -0.347 | |
| *t*-statistic | -2.219 | -2.743 | -2.832 | -2.420 | -2.974 | |
| Panel G: Commodities | | | | | | |
| | Lo ret | 2 | 3 | 4 | 5 | Hi ret |
| Mean Return | -0.560 | -0.373 | -0.041 | 0.210 | 0.432 | 0.879 |
| *b* | -0.551 | -0.693 | -0.712 | 0.264 | -0.813 | -1.502 |
| *t*-statistic | -1.198 | -1.215 | -1.710 | 0.683 | -1.694 | -1.979 |
| Panel H: Currency portfolios (Carry trade) | | | | | | |
| | Low int | 2 | 3 | 4 | 5 | Hi int |
| Mean Return | -0.348 | -0.079 | 0.022 | 0.192 | 0.173 | 0.441 |
| *b* | -0.181 | -0.420 | -0.300 | -0.508 | -0.475 | -0.321 |
| *t*-statistic | -0.648 | -1.357 | -1.626 | -2.936 | -2.398 | -1.794 |
| Panel I: Currency portfolios (momentum) | | | | | | |
| | Lo past ret | 2 | 3 | 4 | 5 | Hi past ret |
| Mean Return | -0.211 | 0.069 | 0.056 | 0.185 | 0.262 | 0.620 |
| *b* | -0.336 | -0.340 | -0.402 | -0.407 | -0.348 | 0.013 |
| *t*-statistic | -2.382 | -2.162 | -2.716 | -2.564 | -2.093 | 0.070 |

Notes: This table presents the results of the in-sample univariate regressions when individual portfolios within each asset category are the dependent variable. For each portfolio, the table reports the in-sample *BKASSET* predictive coefficient (*b*) and its associated *t*-statistics as well as the average excess return. For ease of exposition, some asset portfolios are reconstructed from the original set of portfolios, especially when the number of portfolios is high such as for stocks, bonds, options, CDS, and commodities. Panels A and B present the results for the book-to-market and stock portfolios. Panel C presents the results for bond portfolios. The first portfolio contains the 10 government portfolios. The five remaining are the 10 corporate bond portfolios sorted according to their yield. For the other asset categories (except currencies), portfolios are sorted according to their average returns. Panel H presents the results for the six currency portfolios used in Lettau et al. (2014). Panel I presents the results for the six currency portfolios used in Menkhoff et al. (2012).

Table 8: Predicting different Assets: Quarterly Excess Returns

| | 25 FF | | | 20 US Bonds | | | 6 Sov. Bonds | | | 18 Options | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *BKASSET* | *LEVFAC* | *INTCAP* | *BKASSET* | *LEVFAC* | *INTCAP* | *BKASSET* | *LEVFAC* | *INTCAP* | *BKASSET* | *LEVFAC* | *INTCAP* |
| *b* | -1.176 | -0.001 | 0.000 | -0.418 | 0.000 | 0.000 | 0.210 | -0.002 | 0.000 | -0.755 | -0.002 | 0.000 |
| *p*-value | 0.025 | 0.065 | 0.045 | 0.030 | 0.390 | 0.330 | 0.730 | **0.000** | 0.120 | 0.075 | **0.000** | 0.355 |
| *IS-R²* | 0.019 | 0.029 | 0.023 | 0.034 | 0.000 | 0.008 | 0.004 | 0.159 | 0.064 | 0.016 | 0.096 | 0.007 |
| *p*-value | 0.080 | 0.035 | 0.060 | 0.050 | 0.865 | 0.320 | 0.575 | **0.000** | 0.040 | 0.185 | **0.000** | 0.440 |
| *OOS-R²* | -0.010 | -0.009 | -0.038 | -0.132 | -0.114 | -0.035 | 0.377 | -1.082 | -0.033 | -0.088 | -0.045 | -0.100 |
| *p*-value | 0.410 | 0.615 | 0.220 | 0.000 | 0.115 | 0.005 | 0.535 | 0.110 | 1.000 | 0.949 | 0.179 | 0.999 |
| *p*-value | 0.100 | 0.160 | 0.630 | **0.000** | 0.960 | 0.940 | 0.140 | 0.000 | 1.000 | 0.260 | 0.010 | 0.870 |
| Quarters | 160 | | | 148 | | | 60 | | | 103 | | |

| | 20 CDS | | | 23 Commodities | | | 12 FX | | | ALL | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *BKASSET* | *LEVFAC* | *INTCAP* | *BKASSET* | *LEVFAC* | *INTCAP* | *BKASSET* | *LEVFAC* | *INTCAP* | *BKASSET* | *LEVFAC* | *INTCAP* |
| *b* | 0.019 | -0.001 | 0.000 | -0.340 | -0.001 | 0.000 | -0.405 | 0.000 | 0.000 | -0.727 | -0.001 | 0.000 |
| *p*-value | 0.460 | **0.000** | 0.035 | 0.295 | 0.065 | 0.570 | 0.090 | 0.665 | 0.960 | 0.035 | 0.085 | 0.060 |
| *IS-R²* | 0.001 | 0.303 | 0.138 | 0.005 | 0.088 | 0.000 | 0.014 | 0.004 | 0.052 | 0.026 | 0.024 | 0.017 |
| *p*-value | 0.880 | **0.000** | 0.020 | 0.495 | **0.005** | 0.885 | 0.160 | 0.430 | 0.015 | 0.045 | 0.045 | 0.075 |
| *OOS-R²* | 0.255 | -0.740 | -0.028 | 0.027 | -0.048 | -0.013 | -0.135 | -0.006 | -0.023 | -0.022 | -0.013 | -0.078 |
| *p*-value | 0.751 | 0.113 | 0.926 | 1.000 | 0.436 | 0.993 | 0.022 | 0.006 | 0.000 | 0.006 | 0.167 | 0.266 |
| Quarters | 47 | | | 105 | | | 135 | | | 160 | | |

Notes: This table presents the results of in-sample and out-of-sample tests when we use the average quarterly excess return on all assets of an asset class. The independent predictive variables are *BKASSET*, *LEVFAC*, and *INTCAP*. The statistics are defined in Tables 3-4. Quarters indicate the number of quarterly observations in the in-sample tests. For out-of-sample tests, the initial estimation period contains five years of quarterly returns (20 observations).

## Table 9: Predicting Weekly Market Excess Returns

| Variable | | In-sample tests | | Out-of-sample tests | |
|---|---|---|---|---|---|
| | | *b* | *IS-R²* | *OOS-R²* | Δ |
| *BKASSET* | | | | | |
| | estimate | -0.455 | 0.012 | 0.013 | 3.593 |
| | *t*-statistic | -2.864 | | 2.581 | |
| | *p*-value | **0.002** | **0.000** | **0.000** | **0.000** |
| *TBL* | | | | | |
| | estimate | -1.105 | 0.001 | -0.000 | -0.609 |
| | *t*-statistic | -1.574 | | 0.895 | |
| | *p*-value | 0.059 | 0.320 | 0.080 | 0.750 |
| *TMS* | | | | | |
| | estimate | -0.000 | 0.001 | -0.000 | -0.607 |
| | *t*-statistic | -1.136 | | 0.215 | |
| | *p*-value | 0.898 | 0.556 | 0.320 | 0.690 |

Notes: This table presents the results of in-sample and out-of-sample tests when the dependent variable is the weekly market excess return. The independent predictive variables are *BKASSET*, the Treasury bill rate (*TBL*), and the term spread (*TMS*). The statistics are defined in Tables 3-4. Values in bold type indicate significance using the Holm adjustment. The data mining robust critical values for the in-sample *t*-statistic are 1.727 (10%), 2.077 (5%), and 2.709 (1%). The data mining robust critical values for the CW-*t* are 0.736 (10%), 0.901 (5%), and 1.363 (1%). The data mining robust critical values for Δ are 2.567 (10%), 3.588 (5%), and 4.990 (1%). The results for in-sample tests are presented for the period running from the first week of 1973 to the last week of 2015 (2244 observations). The initial estimation period in the out-of-sample tests contain 520 weeks.

Table 10: Pricing different Assets: Comparison with the Intermediary Pricing Variables

| | 25 FF | | | 20 US Bonds | | | 6 Sov. Bonds | | | 18 Options | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *LH* | *HKM* | *AEM* | *LH* | *HKM* | *AEM* | *LH* | *HKM* | *AEM* | *LH* | *HKM* | *AEM* |
| Intercept | 0.015 | 0.004 | 0.014 | 0.001 | 0.001 | 0.001 | 0.003 | 0.000 | 0.001 | 0.005 | -0.024 | -0.001 |
| $t$-stat$_{fm}$ | 3.398 | 1.058 | 3.212 | 2.034 | 4.167 | 1.692 | 1.530 | 0.109 | 0.359 | 1.090 | -4.418 | -0.234 |
| $t$-stat$_{krs}$ | 1.935 | 0.322 | 2.942 | 0.746 | 2.123 | 1.318 | 0.886 | 0.101 | 0.166 | 0.464 | -0.732 | -0.094 |
| *MARKET* | -0.010 | 0.003 | -0.007 | 0.036 | 0.015 | 0.021 | -0.004 | 0.016 | 0.000 | 0.000 | 0.022 | 0.004 |
| $t$-stat$_{fm}$ | -2.040 | 0.560 | -1.427 | 2.747 | 2.070 | 4.543 | -0.401 | 2.489 | -0.031 | 0.019 | 3.811 | 0.701 |
| $t$-stat$_{krs}$ | -1.225 | 0.224 | -1.339 | 0.785 | 1.070 | 2.574 | -0.310 | 1.911 | -0.011 | 0.010 | 0.644 | 0.299 |
| *INTERM* | -0.006 | 0.018 | 0.021 | 0.006 | 0.013 | 0.069 | -0.007 | 0.014 | -0.171 | -0.006 | 0.237 | -0.128 |
| $t$-stat$_{fm}$ | -4.264 | 1.513 | 0.603 | 1.727 | 0.793 | 2.436 | -2.380 | 1.248 | -2.965 | -4.815 | 4.953 | -3.996 |
| $t$-stat$_{krs}$ | -3.193 | 0.569 | 0.108 | 0.467 | 0.424 | 0.995 | -1.137 | 0.612 | -1.186 | -1.672 | 0.943 | -1.656 |
| $R^2$ | 0.661 | 0.255 | 0.193 | 0.840 | 0.802 | 0.827 | 0.863 | 0.607 | 0.832 | 0.960 | 0.955 | 0.934 |
| $p(R^2=0)$ | 0.016 | 0.317 | 0.567 | 0.012 | 0.002 | 0.001 | 0.011 | 0.074 | 0.025 | 0.000 | 0.000 | 0.000 |
| $p(R^2=1)$ | 0.373 | 0.002 | 0.001 | 0.272 | 0.013 | 0.159 | 0.108 | 0.004 | 0.155 | 0.002 | 0.587 | 0.000 |
| Months | 480 | | | 444 | | | 180 | | | 309 | | |

| | 20 CDS | | | 23 Commodities | | | 12 FX | | | ALL | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *LH* | *HKM* | *AEM* | *LH* | *HKM* | *AEM* | *LH* | *HKM* | *AEM* | *LH* | *HKM* | *AEM* |
| Intercept | 0.000 | -0.002 | -0.001 | -0.001 | 0.000 | -0.001 | -0.004 | -0.003 | -0.006 | 0.000 | 0.002 | 0.001 |
| $t$-stat$_{fm}$ | -0.841 | -6.833 | -5.771 | -0.494 | -0.135 | -0.406 | -2.944 | -2.187 | -4.257 | 0.366 | 1.621 | 0.696 |
| $t$-stat$_{krs}$ | -0.417 | -2.112 | -3.540 | -0.250 | -0.084 | -0.244 | -1.186 | -0.474 | -1.853 | 0.249 | 1.325 | 0.473 |
| *MARKET* | 0.034 | -0.001 | 0.028 | -0.003 | 0.003 | -0.006 | 0.057 | 0.031 | 0.064 | 0.000 | 0.000 | 0.000 |
| $t$-stat$_{fm}$ | 5.074 | -0.193 | 4.259 | -0.405 | 0.477 | -0.835 | 4.785 | 2.599 | 6.244 | -0.003 | 0.028 | 0.055 |
| $t$-stat$_{krs}$ | 2.717 | -0.026 | 1.154 | -0.274 | 0.308 | -0.466 | 2.275 | 0.493 | 1.795 | -0.003 | 0.029 | 0.058 |
| *INTERM* | 0.010 | 0.055 | 0.050 | -0.005 | -0.008 | -0.111 | 0.008 | 0.070 | 0.080 | -0.004 | 0.010 | -0.069 |
| $t$-stat$_{fm}$ | 4.963 | 5.294 | 1.205 | -2.435 | -0.629 | -2.657 | 4.780 | 4.681 | 1.644 | -2.416 | 1.003 | -1.615 |
| $t$-stat$_{krs}$ | 3.120 | 1.012 | 0.186 | -1.685 | -0.378 | -1.553 | 1.759 | 2.491 | 0.434 | -1.712 | 0.862 | -1.384 |
| $R^2$ | 0.942 | 0.719 | 0.674 | 0.329 | 0.051 | 0.291 | 0.598 | 0.327 | 0.301 | 0.285 | 0.043 | 0.096 |
| $p(R^2=0)$ | 0.000 | 0.072 | 0.033 | 0.099 | 0.778 | 0.223 | 0.000 | 0.251 | 0.246 | 0.240 | 0.715 | 0.489 |
| $p(R^2=1)$ | 0.920 | 0.128 | 0.018 | 0.794 | 0.140 | 0.724 | 0.015 | 0.000 | 0.000 | 1.000 | 1.000 | 1.000 |
| Months | 143 | | | 316 | | | 406 | | | 107 | | |

Notes: This table presents the results of asset pricing tests by asset class. Three models are examined the *LH*, *HKM*, and *AEM* models. They are the two-factor models including market excess returns (*MARKET*) and one of the three intermediary pricing factors (*INTERM*), which are *BKASSET, INTCAP* and *LEVFAC*, respectively. Each column presents the risk premia, the Fama and MacBeth (1973) $t$-statistics ($t$-stat$_{fm}$), the Kan et al. (2014) $t$-statistics that accounts for potentially misspecification ($t$-stat$_{krs}$), the cross-sectional goodness-of-fit measure ($R^2$), and the $p$-values associated with the $R^2$=0 and $R^2$=1 test.

Table 11: Pricing different Assets: *BKASSET* with other Risk Factors

| | Carhart | PS | FF5F |
|---|---|---|---|
| Intercept | 0.001 | 0.001 | 0.001 |
| $t$-stat$_{fm}$ | 1.497 | 1.424 | 1.306 |
| $t$-stat$_{krs}$ | 1.011 | 0.923 | 0.803 |
| *MARKET* | -0.003 | -0.003 | -0.002 |
| $t$-stat$_{fm}$ | -0.578 | -0.578 | -0.498 |
| $t$-stat$_{krs}$ | -0.553 | -0.556 | -0.480 |
| *SMB* | 0.007 | 0.006 | 0.007 |
| $t$-stat$_{fm}$ | 2.032 | 2.034 | 2.238 |
| $t$-stat$_{krs}$ | 1.813 | 1.832 | 2.017 |
| *HML* | 0.006 | 0.006 | 0.005 |
| $t$-stat$_{fm}$ | 1.601 | 1.570 | 1.162 |
| $t$-stat$_{krs}$ | 1.354 | 1.314 | 0.910 |
| *CMA* | | | 0.005 |
| $t$-stat$_{fm}$ | | | 1.352 |
| $t$-stat$_{krs}$ | | | 0.965 |
| *RMW* | | | 0.007 |
| $t$-stat$_{fm}$ | | | 1.678 |
| $t$-stat$_{krs}$ | | | 1.469 |
| *MOM* | 0.006 | | |
| $t$-stat$_{fm}$ | 0.447 | | |
| $t$-stat$_{krs}$ | 0.350 | | |
| *LIQ* | | -0.003 | |
| $t$-stat$_{fm}$ | | -0.237 | |
| $t$-stat$_{krs}$ | | -0.180 | |
| *BKASSET* | -0.004 | -0.004 | -0.004 |
| $t$-stat$_{fm}$ | -2.730 | -2.564 | -2.782 |
| $t$-stat$_{krs}$ | -1.971 | -2.039 | -2.186 |
| $R^2$ | 0.482 | 0.514 | 0.495 |

Notes: This table presents the results of monthly cross-sectional asset pricing tests for all asset classes when we include *BKASSET* in the Carhart (1997) model, the Pastor and Stambaugh (2003) model (PS), and the Fama and French five-factor model (FF5F) comprising the three factors used by Fama and French (1993) plus the profitability and investment factors (*RMW* and *CMA*, respectively*)* whose data are obtained from French's website. The statistics are defined in Table 10.

**Appendix A. Computing the data mining robust critical value**

*In-sample tests*

We generate data from equations (2)–(3) as for the computation of the bootstrap $p$-value described in Section 3.1. After estimating the parameters of equations (2)–(3) by OLS and extracting the innovation processes, we generate 10,000 bootstrapped pseudo-series of market excess returns and the ten forecasting variables. For each simulation $l$, we perform a forecasting regression for each factor as follows:

$$r^{l}_{m,t+1} = a^{l}_{j} + b^{l}_{j} X^{l}_{j,t} + \varepsilon^{l}_{j,t+1} \qquad l = 1...L \qquad j = 1...K \qquad \text{(A1)}$$

$L$ is the number of simulations, which is equal to 10,000 here. We compute the Newey-West $t$-statistics on the forecasting coefficient for each factor $t^{l}_{b_j}$. Among these ten Newey-West $t$-statistics, we store the maximal value. We replicate this procedure 10,000 times. The output is an empirical distribution for the maximal $t$-statistic. The actual $t$-statistics are compared to the empirical distribution of the maximal $t$-statistic. We select the 9000th, 9500th, and 9900th values as the 10%, 5%, and 1% critical values for the maximal $t$-statistic.

*Out-of-sample tests*

After generating the pseudo series and performing in-sample regressions (A1) to find the bootstrap predictive coefficients $b^{l}_{j}$, we compute the bootstrapped out-of-sample forecasts as well as the associated $CW\text{-}t^{l}_{j}$ and economic value measure $\Delta^{l}_{j}$ using each factor. In each simulation, we also store the highest $CW\text{-}t^{l}_{j}$ and the highest $\Delta^{l}_{j}$ among the ten out-of-sample regressions. The bootstrap $p$-values are computed as the proportion of the simulated statistics that are greater than the actual statistics. The 9000th, 9500th, and 9900th values of the empirical distribution of the maximal CW-$t_j$ and $\Delta_j$ serve as the 10%, 5%, and 1% critical values for each maximal statistic.

## Appendix B. The Holm adjustment

The Holm adjustment is a sequential method whose purpose is adjusting *p*-values in multiple hypothesis testing to avoid identifying one or more factors to be significant while they are not (the probability of at least one Type I error). The null hypotheses subject to investigation are that the $K$ predicting variables are not significant (one by one).

The Holm adjustment is implemented as follows:

Step 1: Perform a forecasting regression for each of the $j$ factors ($j$=1..$K$) and store the *p*-value corresponding to the null hypothesis that factor $j$ does not predict returns.

Step 2: Order the original *p*-values. Let $p_1$ and $p_K$ be the smallest and highest *p*-values and note the corresponding null hypotheses as $H_1$ and $H_K$, respectively.

Step 3: Compute the adjusted *p*-value for each factor as follows:

$$adj\ p = \frac{\alpha_w}{(K+1-q)} \tag{A2}$$

where $\alpha_w$ is the significance level (set at 5%) and $q$ is the order of the *p*-value from lowest to highest. Notice that the adjusted *p*-values are ordered naturally from lowest to highest.

Step 4: Let $k$ be the index corresponding to the factors from which the ordered original *p*-values exceed the adjusted *p*-values. Reject null hypotheses $H_1 \ldots H_{k-1}$, which means that the associated factors are declared significant, whereas those related to hypotheses $H_k \ldots H_K$ are not.

*Example of implementing the Holm adjustment*

As an example, we take the results of the in-sample regressions, which are displayed in the second column of Table 4. We consider the bootstrap *p*-value computed for each factor as described in Section 3.1.

The following table corresponds to the null hypotheses that forecast coefficients $b_j=0$ $j=1\ldots K$

| Reordered tests q | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Old order | 1 | 4 | 7 | 10 | 2 | 9 | 6 | 3 | 5 | 8 |
| Factor name | *BKASSET* | *SVAR* | *TBL* | *INFL* | *LOGDY* | *DFY* | *NTIS* | *LOGEP* | *BM* | *TMS* |
| *p*-value | **0.000** | 0.040 | 0.098 | 0.112 | 0.155 | 0.239 | 0.385 | 0.501 | 0.696 | 0.759 |
| adj *p* | **0.005** | 0.006 | 0.006 | 0.007 | 0.008 | 0.010 | 0.013 | 0.017 | 0.025 | 0.050 |

From factor 2, the original *p*-values exceed the adjusted *p*-values, so we reject null hypothesis $H_1$, which means that the first factor (*BKASSET*) is significant, whereas the other factors are not.

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