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Foreign Exchange Dealer Asset Pricing

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Abstract

We show that excess returns to the carry trade can be interpreted as compensation for foreign exchange dealers' capital risk. Given that the top market makers in foreign exchange are at the heart of the market's information aggregation process we also suggest that it is their marginal value of wealth which prices foreign currencies. Consistent with this hypothesis the empirical results show that shocks to the equity capital ratios of the top three foreign exchange dealers have explanatory power for the cross-sectional variation in expected currency market returns, while those of the average dealer provide no substantial additional information.

Keywords: Carry Trades, FX Dealers, Currency Risk, Intermediary Asset Pricing

JEL classification: F31, G12, G15.

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1 Introduction

The foreign exchange (FX) market with a turnover of 5,067 billion US dollar in 2016 (BIS 2016) can be considered as the biggest over-the-counter (OTC) market in the world, where a set of specialized dealers provide FX liquidity for a large variety of customers and trade heavily among each other. Particularly large foreign exchange dealers may be perceived as internationally-active financial intermediaries potentially being marginal for pricing FX assets. This is supported by the fact that they are at the core of the FX dealing process, face low transaction costs, and make use of complex investment strategies as well as extensive data resources. These properties nicely fit the underlying assumptions of consumption-based asset pricing models regarding the sophisticated representative investor and his optimizing behavior. Thus, it is the marginal value of wealth of large FX dealers which may propagate a stochastic discount factor instead of the marginal value of wealth of the representative household. Regarding the intermediaries' specific metric for asset pricing information in general recent empirical contributions stress the importance of balance sheet variables for explaining the cross-section of excess returns in a number of asset classes (He, Kelly, and Manela 2017; Adrian, Etula, and Muir 2014).[1]

This paper provides a detailed analysis of the role of FX dealers' balance sheet constraints for currency pricing. Our empirical results show that their aggregated capital ratio performs remarkably well as a priced risk factor in a variety of currency portfolios. The key insight, however, arises from ranking data we collected from the EuroMoney FX survey. In fact, balance sheet information of the reported biggest three FX dealers by market share is sufficient to describe the cross-sectional variation of currency portfolio returns. Factor horse races reveal that this factor outperforms the factor calculated from the broader set of financial intermediaries listed as the New York Fed's primary dealers as used in He et al. (2017).

From a theoretical perspective, the results nicely fit the specific two-tier over-the-counter structure of foreign exchange markets. The first tier consists of a dealer-to-customer trading segment, where dealers trade foreign exchange with their clients such as importers, exporters, and international investors. The second tier refers to an dealer-to-dealer trading segment confined to FX dealers operating among themselves (Lyons 1995). The information dissemination is assumed to start with customers reacting to macro news by submitting orders to their FX dealers. The excess of all buying and selling orders from customers of a given dealer is then transferred to the dealer-to-dealer segment of foreign exchange (Lyons 1997).[2] This market structure suggests that information aggregation may be time consuming (Evans and Lyons 2005; Love and Payne 2008). More importantly, however, the market structure implies that the size of the dealer matters for FX pricing as large dealers represent a substantial fraction of the overall order flow. In addition, large dealers typically dominate the dealer-to-dealer trading thereby also attracting a major share of other dealers' order flow. The predictions for dealers' balance sheet measures

[1] Note that banking regulation, which impacts dealers' balance sheets has been shown to significantly constrain their position taking in FX markets (Du, Tepper, and Verdelhan 2018).

[2] More recently, Malamud and Schrimpf (2018) develop a general equilibrium model with FX dealers being marginal investors in international financial markets. The consideration of market frictions such as dealers' market power in dealer-to-customer trading helps to explain the role of the US dollar as a safe haven currency and the recently observed departures from covered interest parity.

are straightforward. The average (periphery) dealer is able to hand over her exposure from FX trading to major (core) dealers functioning as the ultimate liquidity providers (Moore, Schrimpf, and Sushko 2016). Moreover, core dealers tend to take risks on their balance sheets from their FX business instead of engaging in the hot potato. This is suggested by survey evidence discussed in Moore et al. (2016) and confirmed by Hasbrouck and Levich (2019) using CLS settlement data. To quote from Moore et al. (2016): *'The top-tier dealer banks that intermediate the lion's share of customer flows have maintained their position as large flow internalisers, price-makers and liquidity providers.'* If balance sheet effects of FX trading is neutralized for periphery dealers, but not for core dealers, then capital ratios of core dealers should contain most of the information relevant for FX pricing, while those of periphery dealers are less likely to be informative. Our empirical results provide support for this hypothesis showing that excess returns in currency markets are well explained by the financial wealth of the three most active FX dealers who are the relevant marginal dealers, while the additional explanatory power from including more peripheral dealers' capital ratios is negligible.

Aside from providing insights into the pricing ability of top-tier dealers for currency portfolio returns, we extend the analysis by performing empirical asset pricing tests separately on cross-sections sorted by carry, momentum and value. In particular, our intermediary asset pricing models show a remarkably good fit for carry trade portfolios. This points towards a risk-based explanation of carry trade returns related to balance-sheet conditions of main FX dealers. Currencies trading at a high forward discount tend to pay off poorly when the capital ratio decreases and balance sheet constraints are tightening. In contrast, the negative beta of currencies with a forward premium suggests that these provide a hedge for times of a decreasing capital ratio. With respect to other portfolio sorts, however, little pricing ability of the intermediary factors is found to explain value portfolios and almost none for currency portfolios sorted on exchange rate momentum implying that these portfolios seem to exert little impact on core FX dealers' balance sheets. The missing evidence fits the recent literature on currency risk factors reporting that factors which matter for carry trade pricing are less successful in explaining currency momentum returns (Menkhoff, Sarno, Schmeling, and Schrimpf 2012b).

Our findings contribute to several strands in the finance as well as economics literature. Recent contributions in macro-financial modeling point to the importance of balance sheet variables of financial intermediaries for asset returns. He and Krishnamurthy (2013) as well as Brunnermeier and Sannikov (2014) propose models in which financial intermediaries face equity constraints affecting risk premia when binding. Examples of models taking leverage constraints into consideration are Brunnermeier and Pedersen (2009) as well as Adrian and Boyarchenko (2012). Extending a banking economy with financial frictions to a two-country model, Maggiori (2017) analyzes the role of intermediaries for international risk sharing. More closely related to our set up is Malamud and Schrimpf (2018) who provide a fully micro-founded general equilibrium model in which top FX dealers are the relevant marginal investors.

The predictions of the above discussed intermediary asset pricing theories concerning the price of risk associated with intermediaries' balance sheets differ substantially. Whereas theories that favor intermediaries net worth as state variable find intermediary equity to be procyclical, theories emphasizing the role of leverage predict procyclical intermediary leverage implying countercyclical net worth behavior. Our empirical results favor procyclical intermediary equity in foreign exchange risk premia.

In the empirical intermediary asset pricing literature, Adrian et al. (2014) find that a factor model with innovations to broker-dealer leverage being the only factor is able to price stock and bond portfolios with a remarkable R^2 of about 77% outperforming standard multi-factor models. Adrian, Moench, and Shin (2016) extend this result to a dynamic framework allowing risk prices to be driven by lagged intermediary balance sheet variables as proposed by the theoretical contributions discussed above. He et al. (2017) generalize the work of Adrian et al. (2014) to various asset classes using shocks to financial intermediary capital ratios and find significant explanatory power for cross-sectional variation in excess returns. Their capital ratio factor which is also used in our work is found to be pro-cyclical and would therefore imply the corresponding leverage to be counter-cyclical. This is in contrast to the positive price of leverage risk observed in Adrian et al. (2014) as well as Adrian et al. (2016).

With respect to our application to FX markets it is important to note that intermediaries' balance sheet factors matter most for those asset markets, which are highly intermediated (Haddad and Muir 2018). However, direct empirical evidence from FX markets is relatively scarce. Adrian, Etula, and Groen (2011) provide evidence that balance sheet variables have an impact on the price of market risk in foreign exchange. Closest to our analysis is He et al. (2017) who demonstrate that capital ratio innovations from a broad set of the Federal Reserve's primary dealers are a priced risk factor in many asset classes. Although the authors also provide results for the cross-section of currency portfolio returns sorted on carry and momentum, the main purpose of their paper is to show the universal pricing power of balance sheet factors for a maximum variety of assets. However, our empirical evidence from FX markets suggests that primary dealers are not a homogeneous group of intermediaries equally important on every asset market. Instead, considering the specific OTC nature of FX trading as outlined above, we show that capital ratio innovations of the three largest dealers are sufficient to describe excess FX returns, but not excess returns on other asset markets.

Our work is further related to the recent research agenda on covered interest parity (CIP) deviations, that are mainly devoted to changes in banking regulation (Du et al. 2018, Borio, McCauley, McGuire, and Sushko 2016, Avdjiev, Du, Koch, and Shin 2016). Du et al. (2018) argue that post-crisis balance sheet regulations constrain financial intermediaries resulting in an inelastic supply of currency hedging and therefore leave arbitrage opportunities due to CIP deviations unexploited. Aside from regulatory issues funding liquidity premia, which differ across currency areas may be key to understand CIP deviations. In fact, Rime, Schrimpf, and Syrstad (2019) report substantial differences in USD funding costs implying that only very few intermediaries are able to gain significant arbitrage profits. Moreover, Andersen, Duffie, and Song (2019) emphasize the role of funding value adjustments covered in quoted dealer prices due to debt overhang costs to their shareholders. They argue that the dealer's credit spread must be exceeded by the cross-currency basis to make them benefit from arbitraging CIP deviations.

Another important strand of the literature focuses on risk factors in the cross-section of currency returns. For instance, Lustig, Roussanov, and Verdelhan (2011) find that this cross-section can be largely explained by only two principal components, where the first one can be interpreted as a currency market return[3] and the second factor can be identified as a slope factor that is closely related to a high-minus-low carry trade return.[4] The use of linear factor models with the dollar risk factor and a second slope factor gained popularity in subsequent literature focusing on currency market risks. Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) propose a measure of global FX volatility as an alternative slope factor that has a significantly negative price of risk. Mueller, Stathopoulos, and Vedolin (2017) show another way to extract information from currency moments by observing that the cross-sectional dispersion of FX correlations widens in market downturns. A factor measuring the dispersion of FX correlations is found to serve well as a slope factor for pricing currency portfolios. Lettau, Maggiori, and Weber (2014) stress the role of downside risk to explain the cross-section of carry trade returns. Further risk factors in currency returns that have been investigated are currency momentum (Menkhoff et al. 2012b; Asness, Moskowitz, and Pedersen 2013) and illiquidity (Mancini, Ranaldo, and Wrampelmeyer 2013; Karnaukh, Ranaldo, and Söderlind 2015). A common feature of most factors studied so far is that they are specific to the currency market and excert only little pricing power in other asset classes. Conversely, typical risk factors from stock markets for example only have very limited pricing power for currency returns (Burnside 2012). We particularly contribute to this literature by investigating FX dealer balance sheet factors as an alternative slope factor that carries an intuitive economic interpretation. The ability of the factor to explain excess returns on FX markets is surprising given that in contrast to many competitor slope factors it is calculated from exogenous sources and not from the time series of FX returns themselves.

The paper is organized as follows. Section 2 briefly outlines the idea of the risk-based explanation of excess returns in currency markets and the connection to intermediary asset pricing. Section 3 discusses our data set, the construction of our top FX dealer factors and explains how currency portfolios are constructed. In Section 4 we present our empirical results. Section 5 concludes.

2 Currency Returns and Intermediary Asset Pricing

Throughout the paper we think of an financial intermediary with an accounting framework based on US dollars.[5] The continuously compounded return of investing one dollar in a foreign currency from periods t until $t+1$ via a FX forward contract can be derived as

$$rx^i_{t+1} \approx f^i_{t,t+1} - s^i_{t+1}, \tag{1}$$

where s^i_t denotes the logarithmic spot exchange rate for exchanging one US dollar to currency i in period t and $f^i_{t,t+1}$ is the corresponding logarithmic forward rate. In a simple two-period consumption-based asset pricing model where the representative investor max-

[3] Typically called 'dollar risk factor' as it is computed as the return from investing on dollar into an equally weighted portfolio of all currencies available.

[4] In the classical high-minus-low carry trade strategy the investor buys the portfolio of currencies with the highest interest rates and finances this purchase with a short position in the lowest interest rate currency portfolio.

[5] The assumption is clearly satisfied for US intermediaries. However we mostly consider internationally-acting financial institutions that are also likely to base decisions on US-dollar-denoted payoffs.

imizes an utility function $U(c_t, c_{t+1}) = u(c_t) + \beta u(c_{t+1})$, and faces a consumption stream c_t, c_{t+1}, the first order condition would imply that

$$0 = \mathbb{E}\left(\beta \frac{u'(c_{t+1})}{u'(c_t)} rx_{t+1}\right), \tag{2}$$

where the price on the left-hand-side is zero because the investment strategy generating the return in (1) is self-financing. Hence the stochastic discount factor (SDF) $m_{t+1} = \beta u'(C_{t+1})/u'(C_t)$ that determines the price of the asset depends on the investor's marginal value of wealth. If we interpret the consumption-based model from the point of view of a financial intermediary, it is reasonable to assume that the marginal value of wealth depends on the intermediaries wealth level that in turn depends on aggregate wealth of the economy as well as the composition of the intermediaries balance sheet. Most financial intermediary theories therefore suggest the SDF being an affine-linear function of aggregate wealth in the economy W_t and a proxy for the wealth of the intermediary sector I_t, or more precisely $m_t = 1 - b^W(W_t - \overline{W}) - b^I(I_t - \overline{I})$, with $\overline{W}$ and $\overline{I}$ being the respective means. Such a pricing kernel would then yield the following linear representation for the expected excess return:

$$\begin{aligned}
\mathbb{E}_t(rx_{t+1}) &= b^W \mathbb{E}_t(rx_{t+1}(W_{t+1} - \overline{W})) + b^I \mathbb{E}_t(rx_{t+1}(I_{t+1} - \overline{I})) && (3)\\
&= b^W Cov_t(rx_{t+1}, W_{t+1}) + b^I Cov_t(rx_{t+1}, I_{t+1}) && (4)\\
&= \beta_t^W \lambda_t^W + \beta_t^I \lambda_t^I && (5)
\end{aligned}$$

with $\beta_t^W = Cov_t(rx_{t+1}, W_{t+1})/Var_t(C_{t+1})$,$\beta_t^I = Cov_t(rx_{t+1}, I_{t+1})/Var_t(C_{t+1})$ denoting the vector of risk exposures of the asset to the corresponding factor and λ_t^W,λ_t^I being the associated prices of risk.

Lustig et al. (2011) find that the cross-section of currency returns can be explained by two principal components and therefore favor a two-factor asset pricing model as in (5). The first one can be identified as a constant factor that is highly correlated to the excess return of a equally weighted portfolio consisting of each currency available. We refer to this factor as Dollar factor and denote it with DOL_t. It can be interpreted as an analogue to market return in the stock pricing literature since it gives information about how much return an investor gets for investing in the whole currency market. This interpretation falls in line with the aggregated wealth factor W frequently found in the intermediary asset pricing literature. The second factor can be identified as a slope factor. Lustig et al. (2011) hence propose the "high minus low"-factor HML_t that is the return of the classical carry trade strategy in which the investor buys the portfolio with the highest interest rates and finances this purchase with a short position in the lowest interest rate portfolio. This second factor rationalized from intermediary asset pricing would be the intermediary wealth factor I. If W really captures the same variation in asset prices as DOL we would expect the same to hold for HML and I. In terms of equation (5) we therefore arrive at expectations derived from

$$\mathbb{E}_t(rx_{t+1}) = \beta_t^{DOL} \lambda_t^{DOL} + \beta_t^I \lambda_t^I, \tag{6}$$

where β_t^{DOL} denotes the risk exposure to the Dollar factor and λ_t^{DOL} the associated price of risk.

3 Data

The following sections discuss the construction of FX dealer risk factors and currency portfolios for estimation of the FX intermediary asset pricing framework introduced above.

3.1 Intermediary Capital Ratio Factors

To empirically test the proposed model we apply a risk factor approximating the financial wealth of marginal traders identified by their market share of overall turnover in foreign exchange. As outlined in the introduction the top three FX dealers are assumed to be closest to the core dealers in FX markets acting as ultimate liquidity providers for customers and average dealers.[6] Moreover, as suggested by Moore et al. (2016) and Hasbrouck and Levich (2019) only the top-tier dealers are expected to also warehouse FX inventory risks in their balance sheets, while the average dealer hands over her balance sheet exposure to core dealers.

To capture the market share of FX dealers we rely on data reported in the Euromoney FX survey. The survey is published every year in the Euromoney magazine since 1979.[7] In about the first four months of a year respondents are asked to name their top 20 foreign exchange dealers by volume and the volume they traded with each dealer. This information allows to construct a ranking of the biggest dealers and to estimate their respective market share. As shown in Table 1, a total of 39 financial institutions entered the top ten at least once in the period between 1984 and 2017. Increasingly fierce competition in the market triggered mergers and acquisitions implying that a number of the listed dealers no longer exist. In addition, most of the dealers and in particular the top three are large international banks, among which Citibank, UBS, and Deutsche Bank as well as precursors of JP Morgan Chase (Chase Manhattan, Chemical) played or still play an important role. The increasing importance of core FX dealers can be observed from the estimated market shares displayed in Figure 1.[8] Whereas the biggest three intermediaries maintain a combined share of below 20% in the 1980s, they reach a peak of over 40% market share in 2008. In general, Figure 1 confirms that foreign exchange trading became much more concentrated over time.[9] Aside from pure market share the grouping of dealers is also backed by the correlation of capital ratios among core dealers and between core dealers and periphery dealers. Particularly in the 2000s the correlation of capital ratios is higher than 90% between Barclays, Citigroup, Deutsche Bank, HSBC, RBS, but substantially lower towards dealers like Lehman Brothers or RBC.[10] Reflecting the internationalization of the intermediation business we also observe an overall increasing correlation of capital ratios over time.

[6] We also used top-five and top-ten dealers as a robustness check. The empirical results documented in section 4.5 remain qualitatively unchanged.

[7] The survey has been usually published together with some accompanying articles in the May issue.

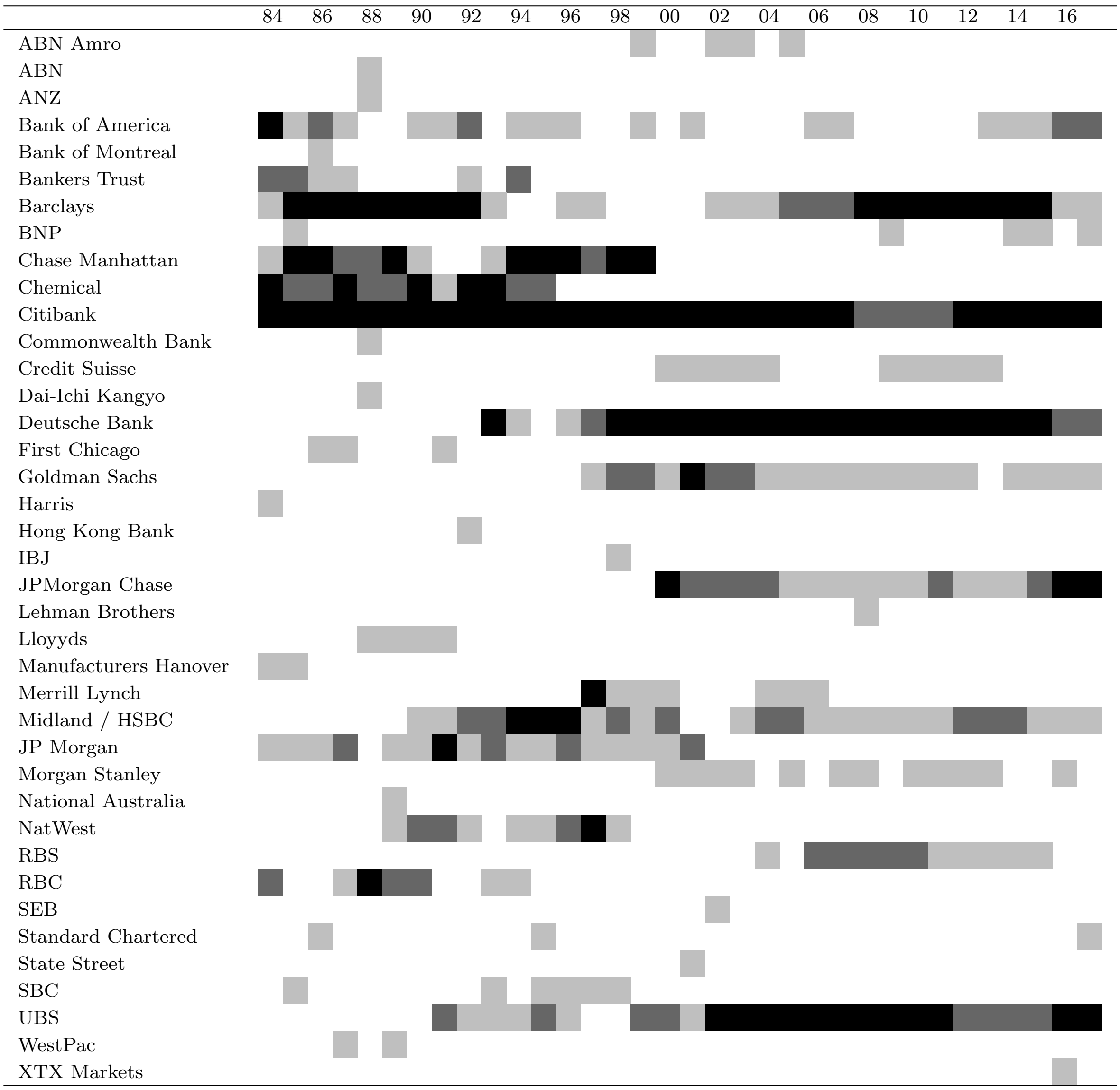
[8] The Euromoney survey articles from 1991 to 1995 do not provide estimates of individual market shares and are therefore linearly interpolated in the figure.

[9] A more detailed picture on FX market concentration can be found in BIS (2010).

[10] An important exception is the capital ratio of UBS with a correlation coefficient of around 70% to most of its top-tier competitor dealers.

Table 1: Top FX Dealer

This table shows the ranks of financial intermediaries in the Euromoney Forex Survey. Boxes indicate whether the intermediary in the given year was ranked within the top ten( ), five ( ) or three ( ) FX dealers by market share.



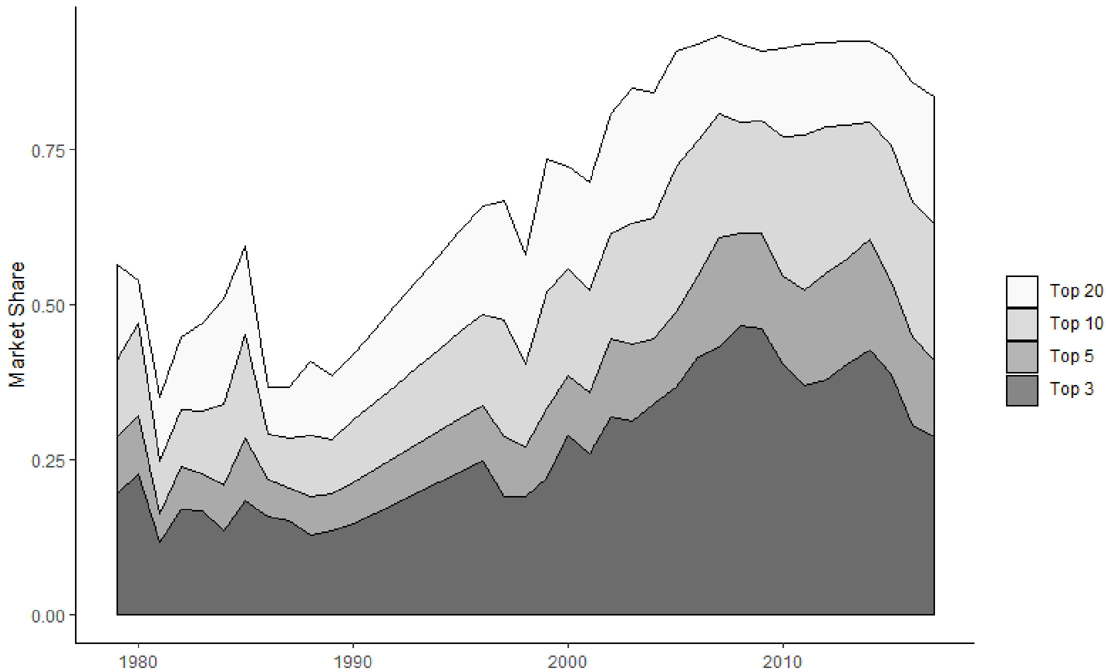


Figure 1: **Market Shares.** The plot shows estimated market shares of top 20, 10, 5 and 3 FX dealers based on the Euromoney Survey. The sample period is 1979 to 2017 with interpolated shares from 1991 to 1995.

Following He et al. (2017) we use balance sheet data on market equity and book debt of FX dealers' holding companies from CRSP/Compustat as well as Datastream. The authors' decision to use balance sheet data of holding companies is driven by the potential importance of intermediaries' internal capital markets. Profit and loss agreements within the financial conglomerates most likely lead to mitigation of shocks to the broker-dealer subsidiary, but show up in the holding company. Conversely, stress situations might be considered where funding for FX exposure of the subsidiary is impaired due to large negative shocks experienced by the holding company. Thus, the aggregate capital ratio of institution i at period t is computed as

$$\eta_{i,t} = \frac{MarketEquity_{i,t}}{(MarketEquity_{i,t} + BookDebt_{i,t})}. \tag{7}$$

To get the market equity we multiply the share price of the stock market where the holding is located with the number of common shares outstanding. The reason for using the market value of equity is that it better reflects whether the intermediary is in financial distress. Due to a lack of availability, book values of debt are used to proxy the corresponding market value. Book debt is computed as total assets minus total common equity of the considered institution. Data for US institutions is obtained from CRSP and from Datastream for all other origins, respectively. Since book debt is available only at a quarterly frequency we use the monthly observation of market equity together with the most recently available quarterly observation of book debt. To be consistent with previous work on carry trade risk premia the empirical analysis is based on monthly frequency, however, the results are qualitatively similar when using quarterly data.

We compute the average capital ratio of the core FX dealers in each month by computing a weighted mean of capital ratios of the three FX dealers' with the biggest market share in foreign exchange trading. These top three FX dealers are identified with the ranking in Table 1 constructed from the Euromoney survey discussed above and the corresponding market shares are used as weights. Since the Euromoney survey appears yearly, the covered dealers and weights are adjusted yearly while the average capital ratio is computed on a monthly basis.[11] Weighting by market share is in line with our idea that core dealers' balance sheets contain the relevant information for asset pricing in the FX market.[12] We also compute the accumulated capital ratio according to He et al. (2017) (HKM) as the average of all holding companies weighted by market capitalization associated with institutions from the New York Fed's primary dealers list. This represents the broadest dealer group incorporating a large number of periphery dealers and allows to compare our results to those of the existing literature. Conversely, every holding company we identify as top FX dealer is simultaneously associated with a New York Fed primary dealer. Hence, our FX dealer factor is also included in HKM.[13]

Figure 2 shows the resulting capital ratios for the core FX dealers as well as the capital ratio derived due to HKM. While the overall development of the two series is quite similar, core FX dealers seem to be equipped with slightly less equity (relative to total assets) most of the time in comparison to the average of all holdings of the New York Fed's primary dealers. Percentage shocks to capital ratios are derived by calculating standardized residuals from fitted AR(1) processes. We denote the time series of shocks to the core FX dealer average capital ratio by $FXcore$ and shocks regarding the broad set of dealers as HKM. As already indicated by the above correlations between single dealers we observe a relatively low correlation coefficient between $FXcore$ and HKM of 0.62. This is surprising given the fact that HKM does contain the capital ratio innovations of the core dealers.

3.2 Exchange Rates and Currency Portfolios

We collected data on spot exchange rates and one-month forward exchange rates of 48 currencies from Thomson-Reuters Datastream with the US dollar being the base currency.[14] The following 48 countries are included: Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Croatia, Cyprus, Czech Republic, Denmark, Egypt, Euro area, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Russia, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Ukraine, and the United Kingdom. The panel of exchange rates covering the period from January 1984 to February 2017 is highly unbalanced with at most 38 currencies being available at the

[11] Missing market shares are linearly interpolated in the period from 1991 to 1995.

[12] Note, however, that alternative weightings in equal shares or by market capitalization do not affect the qualitative results of our following analysis.

[13] The construction of the periphery dealers' balance sheet factor is discussed below.

[14] We additionally performed our empirical exercise with the British pound as well as the Japanese yen as base currency. The results do not differ qualitatively.

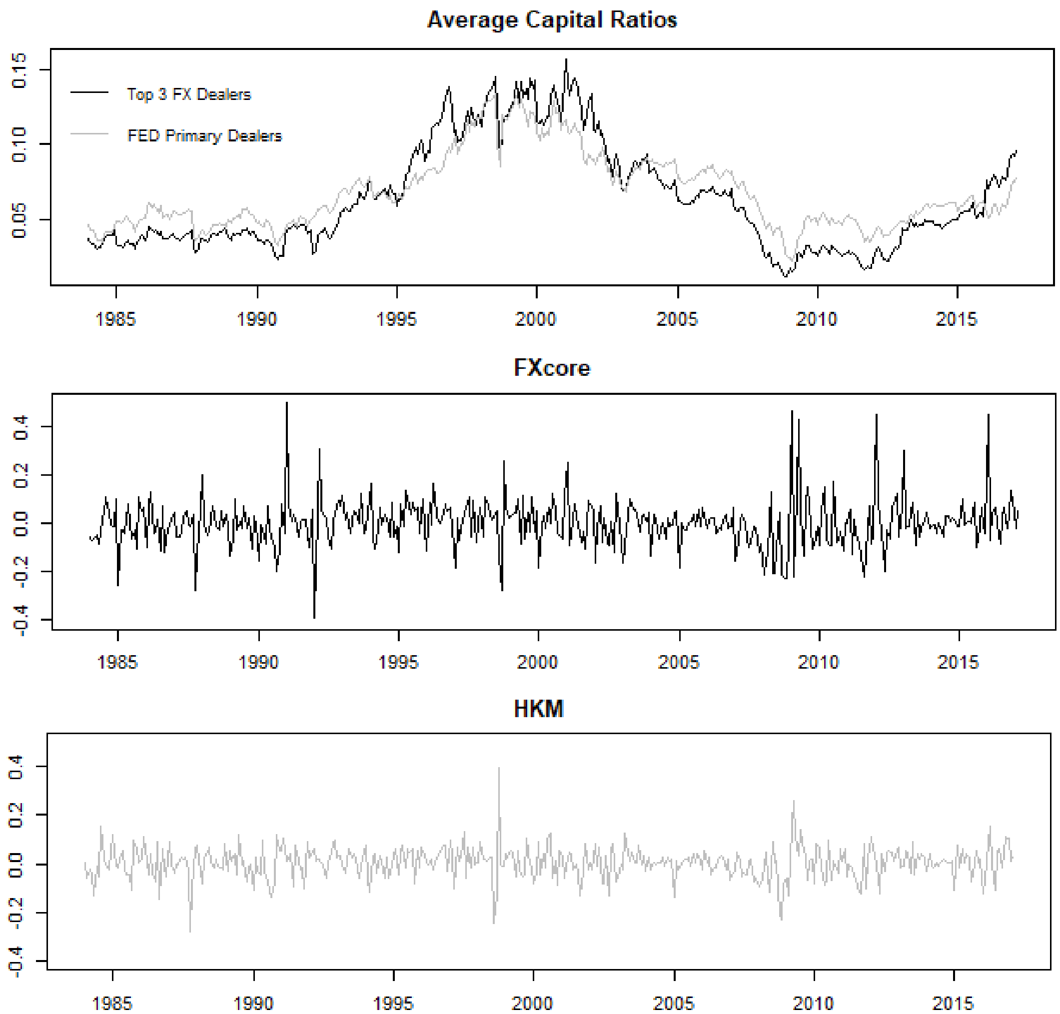


Figure 2: **Capital Ratios and Growth Rates.** The upper plot shows average capital ratios of all New York Fed primary dealers as computed in He et al. (2017) as well as of the top three foreign exchange dealers by market share according to the Euromoney FX survey weighted. The middle and bottom plot show growth rates of the both capital ratio series derived from AR(1)-innovations.

same time. We include the Euro from January 1999 onward and discard currencies of euro-member currencies in following periods.[15]

The choice of currencies in the sample as well as the currency excess returns as computed in eq. (1) is in line with the literature on currency risk factors as, for instance, Lustig et al. (2011) and Menkhoff et al. (2012a). From the panel of exchange rates we build a cross-section of 15 currency portfolios sorted on three different variables. In each period t we sort the currencies with available excess return in $t+1$ on a predefined variable

[15]The introduction of the euro is taken as a cause to provide sub-sample estimates using data ranging from 1999 to 2017.

and allocate them into five quintile portfolios. For every portfolio we then compute the equally weighted excess return for period $t+1$ by taking the average of all currencies allocated to the respective portfolio. To account for transaction costs that emerge from monthly rebalancing the currency portfolios we perform a bid-ask-spread adjustment as in Menkhoff et al. (2012a).

The first five portfolios are sorted on the forward discount as studied in Lustig et al. (2011). We allocate each currency to one of five equally-weighted portfolios sorted by their forward discounts $(f_t^i - s_t^i)$.[16] The first portfolio (C1) therefore includes the fifth of currencies with the lowest interest rate differential to the US interest rates and the fifth portfolio (C5) the fifth of currencies with the highest interest rate differential. Shorting C1 and investing in C5 would then be a classical high-minus-low carry trade strategy.

The second set of five portfolios is sorted on the currencies' excess returns over the previous three months.[17] The first portfolio (M1) therefore includes the fifth of currencies with the lowest excess returns in the previous three months and the fifth portfolio (M5) the fifth of currencies with the highest excess returns in the previous three months. A strategy going short in past losers (M1) and invests in past winners (M5) is known as momentum strategy. This type of currency portfolios is studied in Menkhoff et al. (2012b).

We sort the last five portfolios by real exchange rates. The latter are calculated by dividing nominal exchange rates by purchasing power parity (PPP) conversion factors provided by the OECD. We then allocate each currency to one of five equally-weighted portfolios sorted by their real exchange rate level. The first portfolio (V1) therefore includes the fifth of currencies that are most overvalued with respect to PPP and the fifth portfolio (V5) the fifth of currencies that are most undervalued with respect to PPP.[18] This currency portfolio sort is studied in Menkhoff, Sarno, Schmeling, and Schrimpf (2017).

Merging these three types of portfolio sorts helps to overcome problems of low degrees of freedom in the cross-section since they capture different dimensions of currency risk premiums. Note that all covered types of portfolio sorts are commonly used in FX markets.[19]

Table 2 shows descriptive statistics of the fifteen portfolio return series and the corresponding HML strategy return. We recognize the familiar pattern of carry trade returns that is similar to previous empirical studies (for example Berge, Jordà, and Taylor (2010) and Burnside, Eichenbaum, and Rebelo (2011)) on carry trade returns although we included post-financial crisis times. Monthly average returns and kurtosis increase monotonically from low to high forward discount portfolios whereas the skewness becomes more negative. There is no clear pattern regarding the standard deviation. Panel B shows that investing on recent winners (M5) generates positive returns on average whereas an investment in recent losers currencies yields negative average returns. However, the increase in mean return is unlike carry trades not monotonically increasing. The mean of the high value

[16] This sorting is equivalent to sorting on the interest rate differential if CIP holds.

[17] The construction of momentum portfolios based on the returns over the past three months instead of just one month follows Menkhoff et al. (2012b) and is intended to lower the otherwise high portfolio turnover. Note, however, that the results do not change qualitatively when considering one-month returns.

[18] We derive real exchange rates in terms of US dollar per unit of foreign currency and a value greater (smaller) one can therefore be interpreted as a overvaluation (undervaluation) of the US dollar or a corresponding undervaluation (overvaluation) of the foreign currency.

[19] For example Deutsche Bank offers exchange traded funds that invest according to the considered portfolio sorts as the Global Currency Harvest, the DB Momentum index and the DB valuation index.

Table 2: Descriptive Statistics of Portfolio Returns

This table shows descriptive statistics on log excess returns of five quintile portfolios sorted by carry, momentum and value as well as of the corresponding HML portfolio that is an equally weighted portfolio consisting of a short position in the respective lowest quintile portfolio (1) and a long position in the highest quintile portfolio (5). Returns are monthly from January 1984 to February 2017 and adjusted for transaction costs.

Portfolios	1	2	3	4	5	HML
Panel A: Carry						
Mean	-0.303	0.004	0.205	0.197	0.618	0.921
Median	-0.196	0.058	0.268	0.279	0.932	1.181
Std.dev.	2.437	2.087	2.309	2.416	3.030	2.841
Skewness	-0.113	-0.230	-0.281	-0.652	-0.886	-0.713
Kurtosis	1.282	0.805	1.037	1.970	2.280	1.943
Sharpe	-0.124	0.0002	0.089	0.082	0.204	0.324
Panel B: Momentum						
Mean	-0.202	-0.090	0.088	0.211	0.535	0.737
Median	-0.078	0.144	0.048	0.229	0.607	0.686
Std.dev.	2.848	2.519	2.407	2.409	2.507	2.914
Skewness	-0.470	-0.854	-0.030	-0.121	-0.237	0.101
Kurtosis	3.061	3.378	1.428	1.125	1.693	1.539
Sharpe	-0.071	-0.036	0.037	0.088	0.213	0.253
Panel C: Value						
Mean	-0.009	0.178	0.149	0.250	0.408	0.417
Median	-0.014	0.136	0.351	0.448	0.393	0.327
Std.dev.	2.825	2.664	2.522	3.017	2.640	1.510
Skewness	-0.274	-0.061	-0.666	-0.637	-0.238	0.489
Kurtosis	0.674	0.092	3.747	2.121	1.168	1.801
Sharpe	-0.003	0.067	0.059	0.083	0.154	0.276

portfolio (V1) displayed in Panel C is about zero, but positive average returns are granted from investing in the undervalued currency portfolio (V5). All three HML strategies generate positive excess returns on average with Sharpe ratio highest for carry trades and lowest for the value strategy.[20]

4 Empirical Analysis

The following sections present the empirical results establishing a superior pricing power of the $FXcore$ factor compared to a factor covering the wealth of the financial intermediary sector in general. Asset pricing tests concerned as main results follow in the next subsection. Afterwards, further subsections enhance the analysis and provide further robustness.

4.1 Asset Pricing Tests

We begin to investigate the pricing ability of the capital ratio factors by conducting traditional asset pricing tests. Following Burnside (2011) a GMM framework is employed that reproduces traditional two-step estimates as in the spirit of Fama and MacBeth (1973). The first set of moment conditions relates the (expected) returns of each portfolio to the dollar risk factor DOL and the intermediary risk factor I via its corresponding risk exposures β_i^{DOL} and β_i^I. These correspond to the time series regressions in Fama and MacBeth (1973) and are in our model given by

$$\mathbb{E}\left(rx_t^i - c_i - \beta_i^{DOL} DOL_t - \beta_i^I I_t\right) = 0, \qquad i = 1, \dots N \tag{8}$$

of excess returns rx_t^i for each portfolio i on the dollar factor of Lustig et al. (2011) to capture long-run trends and the capital ratio risk factor I being either HKM or $FXcore$. The cross-sectional pricing equation (6) is imposed with the moment condition

$$\mathbb{E}\left(rx^i - \lambda^{DOL}\beta_i^{DOL} - \lambda^I \beta_i^I\right) = 0, \qquad i = 1, \dots N \tag{9}$$

where λ^{DOL} and λ^I denote the risk prices of interest to be estimated. The set of moment conditions is then completed by including orthogonality conditions given by:

$$\mathbb{E}\left(\left(rx_t^i - c_i - \beta_i^{DOL} DOL_t - \beta_i^I I_t\right) DOL_t\right) = 0, \qquad i = 1, \dots N \tag{10}$$
$$\mathbb{E}\left(\left(rx_t^i - c_i - \beta_i^{DOL} DOL_t - \beta_i^I I_t\right) I_t\right) = 0, \qquad i = 1, \dots N. \tag{11}$$

The GMM estimator based on conditions (8) to (11) recovers estimates that could also be achieved by estimating the linear regression models corresponding to (8) and (9) as already mentioned above. However, the associated GMM standard errors of the risk price estimates account for uncertainty from pre-estimating betas. To account for heteroscedastic and autocorrelated pricing errors, we compute the long-run covariance matrix of the GMM errors with the heteroscedaticitiy and autocorrelation consistent (HAC) covariance esti-

[20] Menkhoff et al. (2017) show that the Sharpe ratio of currency value strategies may be increased by adjusting for macroeconomic fundamentals. We refrain from this adjustment possibility for keeping our value portfolio returns on a monthly frequency.

mator of Newey and West (1987) with a Bartlett kernel as proposed in Andrews (1991). The following subsections discuss the results of the time series and the cross-sectional conditions, respectively.

4.1.1 Time-Series Results

As indicated in the data section we provide empirical results using two different time periods. The first period covers the full sample between 1984 and 2017, while the second period ranges from 1999 to 2017 to account for the introduction of the euro and the strong market concentration in FX trading observed in the 2000s.[21] For both samples GMM estimates reveal highly significant betas for the dollar factor in a range between 0.9 and 1.2 (with a few outliers exceeding 1.2) confirming the results documented in Lustig et al. (2011).[22] The estimated capital ratio risk exposures are collected in Table 3.

Starting with the five carry trade portfolios we find that beta is monotonically increasing from a negative value for C1 (low interest rate currency) to a positive value for C5 (high interest rate currency). The latter value constitutes a relatively high risk exposure with respect to intermediaries' capital ratio. High interest rate currencies tend to pay off poorly during bad times when the capital ratio decreases and balance sheet constraints are tightening. Instead, the negative sign of the C1 basket beta reveals a hedging capacity of the low interest rate currencies in times of intermediaries' balance sheet distress. This is in line with the view that at least part of the risk premium to the carry trade can be interpreted as a compensation for high exposure to risk associated with intermediaries' balance sheet capacity. The spread between high and low interest portfolio exposure shrinks when specializing the capital ratio factor from a broad set of financial institutions (HKM) to the top three FX dealers ($FXcore$), but remains statistically significant. The overall results are similar in the more recent sample, however, the differences in estimated exposures are less pronounced. Remarkably, the statistical significance of the exposure of HKM to the high interest portfolio C5 weakens, while the exposure of the $FXcore$ remains highly significant. This may point towards an increased relevance of core dealers' balance sheet capacity in recent times as may be expected from the massive increase in market concentration shown in Figure 1.

Estimated exposures of momentum portfolios towards the capital ratio risk factor show no remarkable patterns in either of the considered samples. Betas are generally insignificant except for a negative exposure of the past winners portfolio (M4) in the full sample. The missing evidence fits the recent literature on currency risk factors reporting that factors which matter for carry trade pricing are less successful in explaining currency momentum returns (Menkhoff et al. (2012b)). A distinguished risk factor for explaining momentum returns may arise from political risk as argued by Filippou, Gozluklu, and Taylor (2018). Regarding the exposure of value portfolios to the HKM factor we observe that the overvalued-currencies portfolio V1 has a significantly negative beta whereas moderately undervalued currency portfolios V3 & V4 show significantly positive betas. This observation may stem from the fact that the latter portfolio includes a number of emerging

[21] Considering the period starting in 1999 additionally provides some technical robustness since we circumvent interpolating missing market shares for the factor weighting.

[22] We refrain from reporting the betas for the sake of parsimony, however, the estimates are available from the authors upon request.

Table 3: Capital Ratio Exposures

This table reports estimated capital ratio risk exposures β_i^I and R^2 from two-factor asset pricing models with including the dollar risk factor DOL and a intermediary risk factor I. The latter is derived as averaged capital ratio from dealers covered in the FED primary dealer list as in He et al. (2017) (HKM) or from top three FX dealers ($FXcore$) identified with the Euromoney FX survey. Parameters are estimated with first-stage GMM approach and Newey-West standard errors are shown in parentheses. R^2's are achieved from corresponding time series regressions. Test assets are 15 currency portfolios sorted on carry (C1-C5), momentum (M1-M5) and value (V1-V5).

	01/1984 - 02/2017				01/1999 - 02/2017			
	$FXcore$		HKM		$FXcore$		HKM	
	β^I	R^2	β^I	R^2	β^I	R^2	β^I	R^2
C1	-2.593***	0.696	-4.252***	0.698	-2.666**	0.638	-4.990***	0.642
	(0.791)		(1.072)		(1.106)		(1.647)	
C2	-1.143**	0.774	-1.300*	0.773	-1.287**	0.849	-0.508	0.845
	(0.516)		(0.703)		(0.573)		(0.889)	
C3	0.961*	0.844	1.139	0.843	0.651	0.886	1.088	0.886
	(0.524)		(0.807)		(0.517)		(0.924)	
C4	0.549	0.851	1.006	0.851	0.488	0.886	1.794*	0.888
	(0.459)		(0.681)		(0.609)		(1.070)	
C5	2.227**	0.668	3.406**	0.668	2.814**	0.686	2.616	0.677
	(0.876)		(1.417)		(1.127)		(2.006)	
M1	0.941	0.611	0.860	0.610	0.761	0.693	0.099	0.692
	(0.932)		(1.447)		(1.249)		(2.010)	
M2	0.034	0.766	0.810	0.766	0.432	0.785	2.051	0.788
	(0.676)		(1.316)		(0.860)		(2.146)	
M3	-0.445	0.803	0.151	0.803	-1.213	0.796	0.930	0.793
	(0.787)		(0.872)		(1.239)		(1.116)	
M4	-1.148**	0.806	-1.842**	0.807	-0.670	0.813	-1.770	0.814
	(0.544)		(0.922)		(0.627)		(1.232)	
M5	0.515	0.626	-0.296	0.626	0.385	0.639	-1.379	0.640
	(0.847)		(1.479)		(1.015)		(1.975)	
V1	-0.448	0.849	-2.104**	0.852	-0.596	0.844	-3.233**	0.849
	(0.591)		(0.958)		(0.893)		(1.617)	
V2	-0.931*	0.806	-0.514	0.805	-1.512***	0.809	-0.045	0.805
	(0.537)		(1.085)		(0.571)		(1.306)	
V3	1.175	0.668	4.375***	0.679	0.220	0.804	2.867	0.809
	(0.887)		(1.018)		(1.235)		(1.762)	
V4	2.380***	0.782	4.677***	0.786	2.678***	0.841	5.441***	0.845
	(0.707)		(1.111)		(0.824)		(1.384)	
V5	-0.218	0.816	-2.373***	0.820	1.473	0.759	1.688	0.756
	(0.560)		(0.877)		(1.011)		(1.816)	

*p<0.1; **p<0.05; ***p<0.01

market currencies, which, in times of a global financial downturn, experience substantial capital outflows due to massive cutbacks of balance sheet exposure in industrialized countries. This is in line with Menkhoff et al. (2017) showing that a weak real exchange rate is contemporaneously associated with a high currency risk premium. In such a situation a portfolio of overvalued currencies, typically from industrialized countries, tends to provide a hedge.[23] With regard to the top FX dealer factors we see that the associated exposures are statistically significant in the moderately overvalued and undervalued currency portfolio V2 and V4, respctively. In contrast, the extreme over- and undervalued portfolios seem to be unrelated to the core FX dealers' business.

4.1.2 Cross-Sectional Results

We now address the question as to whether the balance sheet factors of FX dealers are able to explain excess returns of FX assets. For this purpose we refer to Table 4 showing the GMM results of for the cross-sectional moment conditions in (9). As a preliminary result the table reports a positive but insignificant dollar factor risk price, which is in line with other asset pricing studies of currency portfolios (Lustig et al. 2011, Menkhoff et al. 2012a). In contrast, we find that both intermediary capital ratio factors are statistically

Table 4: Cross-Sectional Asset Pricing Tests (Carry, Momentum & Value Portfolios)

The table reports price of risk first-stage GMM estimates λ_t^{DOL} and λ_t^I from the cross-sectional moment condition $\mathbb{E}_t(rx_{t+1}) = \beta_t^{DOL}\lambda_t^{DOL} + \beta_t^I\lambda_t^I$. The asset pricing model comprises a dollar risk factor DOL and an intermediary risk factor I. The latter is derived as averaged capital ratio from dealers covered in the FED primary dealer list as in He et al. (2017) (HKM) or from top three FX dealers ($FXcore$) identified with the Euromoney FX survey. GMM standard errors are obtained by the Newey and West (1987) approach with Bartlett kernel according to Andrews (1991) and are shown in parentheses. R^2's are achieved from corresponding cross-sectional regressions. Test assets are 15 currency portfolios sorted on carry (C1-C5), momentum (M1-M5) and value (V1-V5).

	01/1984 - 02/2017				01/1999 - 02/2017		
	(1)	(2)	(3)		(4)	(5)	(6)
DOL	0.130	0.136	0.131		0.096	0.098	0.104
	(0.140)	(0.140)	(0.084)	(0.186)	(0.188)	(0.101)	
$FXcore$	0.097***		0.140**		0.146***		0.152**
	(0.036)		(0.059)		(0.054)		(0.061)
HKM		0.035**	0.024			0.053***	0.040
		0.016	(0.046)			(0.016)	(0.055)
R^2	0.479	0.380	0.522		0.462	0.261	0.478
Adj. R^2	0.399	0.285	0.402		0.380	0.147	0.348

*p<0.1; **p<0.05; ***p<0.01

significant when investigated separately. This holds for the full (columns 1 and 2) sample

[23]The highly undervalued currencies portfolio V5 is statistically insignificant in the most of the cases across samples.

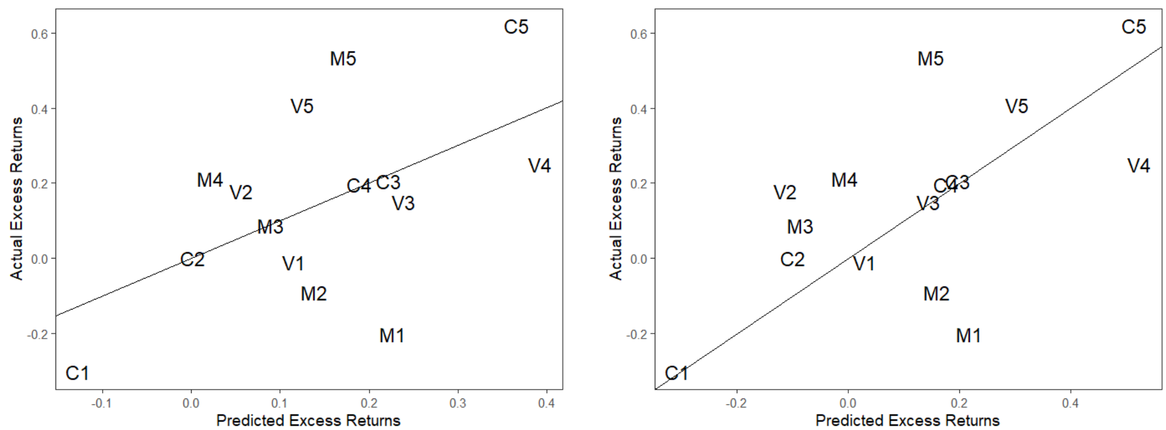
as well as for the more recent period starting in 1999 (column 4 and 5). The exposure of an FX asset to dealer's financial conditions and in particular to those of the core dealers can therefore be seen as a source of risk that needs to be compensated by a premium. The magnitude of the $FXcore$ risk price is more than twice as high as the HKM risk price possibly resulting from the lower magnitude of $FXcore$ betas. This implies that the intermediary risk premium $\beta_i^I \lambda^I$ is roughly the same if measured by $FXcore$ or HKM. However in the recent sample we also see doubled risk price for $FXcore$ although exposures of the high carry portfolio (C5) with respect to the intermediary factors are roughly equal resulting in a higher premium for the $FXcore$ exposure.

The cross-sectional fits of the models lend support for the hypothesis that only core dealers are relevant for FX pricing. The R^2 of the model using $FXcore$ (48%) substantially exceeds the model using the broader set of broker dealers (38%). When considering both factors in a joint model as reported in the third and sixth column the HMK factor turns insignificant. From the adjusted R^2s it can additionally be inferred that the inclusion of the HKM factor does not help to explain variations in the FX test asset returns. This strongly suggests that an FX-specific balance sheet factor as constructed above outperforms a general balance sheet factor as applied in He et al. (2017). In line with the two-tier market structure all useful information contained in dealer balance sheets is provided by a few core dealers warehousing the risk of market making. Having a look on the cross-sectional fit in the sample starting in 1999 that covers periods affected by a strong market concentration we see that the R^2 of the $FXcore$ model remains at the given level, but the R^2 of the model including HKM drops significantly. Again, the inclusion of more balance sheet information from intermediaries with lower market shares in foreign exchange therefore adds more irrelevant noise than additional information explaining currency return cross-sections. This may be interpreted as support for the idea that the specialization of intermediaries matters and we have a currency market SDF that is widely distinct from SDF's of other asset classes.

4.2 Individual Portfolio Cross-Sections

This section gives a more detailed analysis of the cross-sectional fit of the FX intermediary model in individual currency portfolio cross-sections sorted each on carry, momentum or value only. Figure 3 showing the cross-sectional pricing errors for asset pricing models with capital ratio innovations of core FX dealers as a risk factor reveals a strong discrepancy between the cross-sectional fit of different portfolio sorts when included in the same cross-section. Whereas the cross-section of carry trades seem to be well-described by the intermediary model, the relation for momentum portfolios is almost reversed. Running cross-sectional asset pricing tests for portfolios separately sorted on carry, momentum and value provides us with the opportunity to investigate the differences in the cross-sectional fit further. Moreover we can directly compare our results reported in Table 5 with those of the existing literature that mainly focuses on carry trade cross-sections.

The first column of Table 5 shows the results for the five portfolios sorted on carry as it is analyzed in much of the finance literature on carry trades (see, for instance, Lustig et al. (2011) and Menkhoff et al. (2012a)). The risk price of the intermediary balance sheet risk factor is significantly positive. Considering the signs of the risk exposures we can



(a) 01/1984 - 02/2017

(b) 01/1999 - 02/2017

Figure 3: **Pricing Errors.** The figure shows cross-sectional pricing errors for asset pricing models with the dollar return (DOL) and capital ratio innovations of top three FX dealers ($FXcore$) as risk factors.

conjecture that excess returns from the carry trade may be interpreted as a compensation for balance sheet risk. High forward discount currencies tend to pay off badly when the capital ratio decreases and balance sheet constraints are tightening. In contrast, currencies with a forward premium tend to providing a hedge for times of a decreasing capital ratio. The model prices the cross-section of carry trade returns with an R^2 of over 90%. This is remarkable in the sense that the capital ratio risk factor, in contrast to most of the existing competitors in the literature, which also show ability to price carry trades, is not derived from the time series of currency returns itself.[24] In the more recent sample starting in 1999 the $FXcore$ factor shows a similar cross-sectional fit. We can therefore conjecture that in the recent period of financial market stress the balance sheets of the top three FX dealers is still important for pricing carry trades.

For the momentum sorted cross-section in the second column we find no significant estimates of the risk prices at all. The results indicate that FX dealers seem to prevent momentum portfolios to excert an impact on their balance sheets. Moreover, we also refer to the observation in the literature that factors explaining the cross-section of carry trade returns are also unable to price currency momentum returns and vice versa as explored in Filippou et al. (2018).

The third column shows the results for value sorted portfolios where the balance sheet risk prices are found to be positive and significant for the recent sample starting from 1999. The cross-sectional relation is estimated with reasonable levels of R^2. We therefore find that variations in intermediaries' balance sheet capacity can simultaneously explain returns to currency portfolios based carry and value, which capture largely unrelated risk premia as argued by Menkhoff et al. (2017).

[24]For example, Menkhoff et al. (2012a) report a cross-sectional fit of $R^2 = 90\%$ using FX volatility as a priced risk factor.

Table 5: Cross-Sectional Asset Pricing Tests (Individual Portfolio Cross-Sections)

The table reports price of risk first-stage GMM estimates λ_t^{DOL} and λ_t^{FXcore} from the cross-sectional moment condition $\mathbb{E}_t(rx_{t+1}) = \beta_t^{DOL}\lambda_t^{DOL} + \beta_t^{FXcore}\lambda_t^{FXcore}$. The asset pricing model comprises a dollar risk factor DOL and an intermediary risk factor that is derived as the averaged capital ratio from top three FX dealers ($FXcore$) identified with the Euromoney FX survey. GMM standard errors are obtained by the Newey and West (1987) approach with Bartlett kernel according to Andrews (1991) and are shown in parentheses. R^2's are achieved from corresponding cross-sectional regressions. Test assets are separated in three cross-sections consisting of 5 currency portfolios each sorted on carry, momentum or value.

	01/1984 - 02/2017			01/1999 - 02/2017		
	Carry	Momentum	Value	Carry	Momentum	Value
DOL	0.144	0.096	0.163	0.123	0.078	0.107
	(0.136)	(0.133)	(0.130)	(0.174)	(0.175)	(0.162)
$FXcore$	0.167***	−0.070	0.019	0.222***	−0.036	0.074**
	(0.054)	(0.075)	(0.036)	(0.081)	(0.077)	(0.034)
R^2	0.959	0.160	0.668	0.939	0.053	0.572
Adj. R^2	0.932	−0.400	0.447	0.898	−0.579	0.286

*p<0.1; **p<0.05; ***p<0.01

4.3 Individual Currencies

In this section we provide a more detailed analysis of the capital ratio risk factors in explaining FX assets' excess returns using individual exchange rate time series instead of portfolios. We compute returns from investing one US dollar in a single foreign currency and regress them on the DOL and the $FXcore$ intermediary factor. Table 6 shows the corresponding results from regressing individual currency returns on the two risk factors DOL and $FXcore$. We find that typical funding currencies in carry trades like the Swiss franc and Japanese yen have a strikingly-strong negative exposure to capital ratio innovations whereas investment currencies as the Norwegian krone and the Mexican peso show significantly positive betas. This is reflected in the intermediary factor's success in explaining the spread between high and low carry trade portfolios. In addition, currencies of emerging market economies, in our sample particularly the South African rand and the Mexican peso, have positive exposures to balance sheet innovations. These currencies typically show up in the undervalued currency portfolios V4 and V5. In the overvalued portfolio V1 we find primarily the Swiss Franc, Norwegian and Danish krone that have differing significant signs in exposure to our factor. With regard to the momentum strategy, however, we do not have typical winner and loser currencies, but currencies that frequently switch from the long to the short portfolio. These are G10 currencies that either have a positive or negative significant time-series exposure to intermediary balance sheet innovations and can therefore not explain spreads in momentum strategies.

In summary, portfolio sorts based on the carry trade fit the exposures of bilateral exchange rates best. Typical carry currencies additionally enter under- or overvalued

Table 6: Bilateral Currencies Time-series Regressions

This table reports the results from separately estimating regressions $rx_t^i = c_i + \beta_i^{DOL} DOL_t + \beta_i^{FXcore} FXcore_t + u_t^i$ for every series of returns from investing one dollar in a foreign currency. DOL is the return from investing one dollar into an equally-weighted portfolio of all currencies available. $FXcore$ is the AR(1)-innovation from the market-share-weighted capital ratio of top three FX dealers. Newey-West standard errors are shown in parentheses. The sample spans the time period from January 1999 to February 2017.

	c	β^{DOL}	β^{FXcore}	R^2		c	β^{DOL}	βFXcore	R^2
GBP	-0.190*	0.860***	-0.136	0.434	ZAR	0.701*	1.696***	2.732	0.364
	(0.111)	(0.093)	(1.694)			0.424	0.163	3.551	
CHF	-0.168	1.242***	-5.803***	0.614	SGD	-0.081	0.689***	-0.953	0.667
	(0.138)	(0.093)	(1.474)			0.074	0.050	0.817	
JPY	-0.280	0.456***	-6.737***	0.131	HUF	0.027	1.766***	-0.690	0.709
	(0.199)	(0.156)	(2.491)			0.154	0.105	2.943	
CAD	0.001	0.859***	4.128***	0.489	IDR	1.740***	1.143***	2.168	0.153
	(0.106)	(0.066)	(1.161)			0.655	0.180	3.090	
AUD	0.084	1.570***	0.203	0.716	KWD	0.001	0.227***	-1.439***	0.396
	(0.131)	(0.074)	(1.265)			0.033	0.031	0.414	
NZD	0.144	1.568***	-1.102	0.621	MYR	0.925**	0.928***	-0.809	0.194
	(0.155)	(0.096)	(2.099)			0.368	0.107	1.885	
SEK	-0.254***	1.435***	1.464	0.761	MXN	0.109	0.747***	6.173***	0.339
	(0.097)	(0.063)	(1.118)			0.181	0.129	2.124	
NOK	-0.107	1.350***	2.945**	0.707	PHP	0.095	0.450***	0.797	0.234
	(0.108)	(0.104)	(1.837)			0.118	0.056	1.122	
DKK	-0.246**	1.325***	-2.596*	0.777	SAR	0.011	-0.001	0.122**	0.012
	(0.104)	(0.052)	(1.332)			0.008	0.002	0.057	
EUR	-0.259**	1.334***	-2.650*	0.776	TWD	-0.136	0.459***	0.405	0.425
	(0.106)	(0.052)	(1.353)			0.086	0.038	0.807	
HKD	-0.028***	0.013**	-0.018	0.036	THB	0.074	0.488***	0.669	0.276
	(0.010)	(0.007)	(0.128)			0.117	0.057	1.211	

*p<0.1; **p<0.05; ***p<0.01

currency baskets quite often, explaining the satisfactory cross-sectional fit of our model with respect to value portfolios.

4.4 Other Asset Classes

One of the major contributions of differentiating between core and periphery dealers is to show that balance sheet information from the cross section of dealers are not equally important for FX asset pricing. Ideally, we would like to perform similar exercises for core dealers in other asset classes, too. Since data on dealers' market shares are unavailable for a sufficient period of time or not available at all, however, we follow a different strategy. Since entering the group of core dealers may be perceived as a substantial irreversible investment a given financial institution will consider only a few asset markets for its dealer business. Under these circumstances, relevant balance sheet information is concentrated on the core FX dealers only for currency markets and not necessarily for other asset classes. Thus, we may test whether the $FXcore$ factor also exhibits superior pricing power in other asset classes compared to a broad group of broker dealers such as HKM. In particular, the portfolio cross-section from He et al. (2017) is used to run horse races between HKM and $FXcore$.[25] The results presented in Table 7 indicate that in contrast to FX markets, the $FXcore$ factor remains statistically insignificant in other asset markets. Only the HKM factor produces a significant price of risk in case of credit default swaps.

The results generally support the idea of differing pricing powers of balance sheet factors across intermediaries. Although we have mostly information from global banks in our core dealer factor, it is unable to outperform a balance sheet factor derived from a broader group of intermediaries in all other asset classes. This supports the idea of a specific FX pricing factor, although it cannot be ruled out that the top FX dealer are simultaneously important competitors in other classes, too.

4.5 Top-Ten and Top-Five FX Dealers

The heterogeneity hypothesis of FX dealers put forward in the preceding analysis showed that capital ratios of core dealers are informative. Using the largest three dealers was driven by the idea to only include those dealers who receive substantial incoming order flow from periphery dealers and warehouse risks from FX trading in their balance sheets, but this is clearly an arbitrary choice. In fact, the changing degree of competition in the market over time suggests that more dealers might be relevant for FX pricing. Thus, for a further robustness check we additionally compute the $FXcore$ factor using the top-ten as well as top-five dealers. We will call the alternative factors $FXcore5$ and $FXcore10$, respectively. Due to limited availability of balance sheet data for some intermediaries included in the top ten in the 80s and 90s, we report regression results only for the more recent sample.

[25]Returns are quarterly and collected from pre-existing studies: Fama and French (1993) 25 size and value sorted portfolios for equity, ten portfolios sorted on yield spreads from Nozawa (2017) togther with ten maturity-sorted government bond portfolios for US bonds, six sovereign bond portfolios from Borri and Verdelhan (2012), 18 index option portfolios from Constantinides, Jackwerth, and Savov (2013), 20 CDS portfolios sorted by spreads using individual name 5-year contracts with returns defined in accordance with Palhares (2013) and 23 commodity portfolios derived with returns to commodity futures from the Commodities Research Bureau as used in Yang (2013).

Table 7: Factor Horse Races in Alternative Asset Classes

This table reports GMM estimation results of intermediary asset pricing models including a market factor ($Market$), the capital ratio factor from He et al. (2017) (HKM), and the top three FX dealer capital ratio factor ($FXcore$) for cross-sections from different asset classes. GMM standard errors are obtained by the Newey and West (1987) approach with Bartlett kernel according to Andrews (1991) and are shown in parentheses. R^2's are achieved from corresponding cross-sectional regressions. Test assets are from several cross-sections of different asset classes as used in He et al. (2017). The frequency is quarterly and the sample period varies within 01/1984 to 12/2012 depending on the data availability.

	FF25	US bonds	Sov. bonds	Options	CDS	Commod.
$Market$	0.019	−0.039	0.003	0.012	0.008	0.011
	(0.021)	(0.257)	(0.052)	(0.044)	(0.018)	(0.061)
$FXcore$	−0.030	0.474	0.116	0.320	0.013	0.017
	(0.291)	(1.192	(0.097)	(0.915)	(0.035)	(0.199)
HKM	0.057	0.248	0.068	0.196	0.066**	0.057
	(0.080)	(0.595)	(0.058)	(0.359)	(0.027)	(0.110)
R^2	0.934	0.729	0.963	0.992	0.632	0.132
Adj. R^2	0.925	0.682	0.927	0.990	0.566	0.002
Assets	25	20	6	18	20	23
Quarters	116	112	65	103	47	105

*p<0.1; **p<0.05; ***p<0.01

Table 8 shows the cross-sectional results from horse races between the four intermediary

Table 8: Alternative Factor Horse Races

This table reports results of horse races between different intermediary asset pricing model estimated with GMM. The asset pricing models comprises a dollar risk factor DOL and two intermediary risk factors. The latter are derived as averaged capital ratios from dealers covered in the FED primary dealer list as in He et al. (2017) (HKM) or from top ten ($FXcore10$), top five ($FXcore5$), or top three FX dealers ($FXcore$) identified with the Euromoney FX survey. GMM standard errors are obtained by the Newey and West (1987) approach with Bartlett kernel according to Andrews (1991) and are shown in parentheses. R^2's are achieved from corresponding cross-sectional regressions. Portfolios are sorted on carry (C1-C5), momentum (M1-M5) and value (V1-V5). The sample spans the period from January 1999 to February 2017.

	(1)	(2)	(3)	(4)	(5)
DOL	0.120	0.104	0.088	0.098	0.100
	(0.197)	(0.202)	(0.197)	(0.196)	(0.198)
$FXcore$	0.133**	0.142**			
	(0.052)	(0.066)			
$FXcore5$	0.042		0.107**	0.098**	
	(0.046)		(0.051)	(0.049)	
$FXcore10$		0.015	0.068		0.065*
		(0.036)	(0.042)		(0.034)
HKM				0.050**	0.054**
				(0.024)	(0.023)
R^2	0.606	0.732	0.317	0.291	0.267
Adj. R^2	0.508	0.665	0.146	0.114	0.084

*p<0.1; **p<0.05; ***p<0.01

factors considered. Although $FXcore5$ and $FXcore10$ are found to price the currency cross-section, we generally observe that $FXcore$ outperforms the two alternative factors. This indicates that including balance sheet information from additional top FX dealers besides the top three does not improve the asset pricing performance of the FX dealer model. Moreover a general decline in the pricing ability can be observed as the $FXcore5$ pulls the $FXcore10$ factor insignificant in a separate horse race. Taken together, the results of this robustness check lend support to the importance of dealer heterogeneity in OTC markets.

This supports our view that the relevant marginal dealers in foreign exchange whose balance sheet conditions should determine the pricing kernel are the core dealers with the highest market share whereas the periphery dealers do not provide any additional useful information for pricing.

5 Conclusion

Since at least the seminal contribution by Brunnermeier and Pedersen (2009) finanical intermediaries' balance sheets are playing an increasingly important role in describing asset price dynamics, because of their ability to reflect current funding conditions of key players in the market. This implies that broker dealers' balance sheet factors should matter more for highly intermediated assets than for assets that households are willing to hold directly (Haddad and Muir 2018). Given that the foreign exchange market is by far the largest venue for intermediated over-the-counter transactions, FX dealers' balance sheets may be a promising candidate to understand currency excess returns. Indeed, our empirical results confirm that FX dealers' capital ratios perform remarkably well, particularly when it comes to explaining excess return to the carry trade. The key insight of this paper, however, arises from the relaxation of the assumption that FX dealers' balance sheets are equally informative. Considering the specific two-tier over-the-counter structure of foreign exchange markets, where new information contained in customer order flow is aggregated to eventually arrive at the inter-dealer market, the core market makers' balance sheets are expected to be most informative. Our empirical results provide strong support for this heterogeneity hypothesis showing that excess returns in currency markets are superiorly explained by the financial wealth of the three most active dealers making only them the relevant marginal investors.

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