Information Spillovers and Predictable Currency Returns: An Analysis via Machine Learning

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Abstract

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1 Introduction

While the foreign exchange literature has focused on whether the forward rate of a currency forecasts its future spot rate, a growing number of studies show that the forward rate of one currency can forecast the spot rate of another currency (e.g., MacDonald and Marsh (2004); Nucci (2003); Wang, Yang, Wang, and Fawson (2017)). The empirical evidence is consistent with the information spillover effect across currencies in international asset pricing models (e.g., Brandt, Cochrane, and Santa-Clara (2006); Hodrick and Vassalou (2002); Kingston and Melecky (2007); Nucci (2003)).

The prior empirical research, however, has some limitations. First, the pre-selected currency pairs are often chosen in an ad hoc way or for *closeness* in terms of geographical locations and economic relations. Such pre-selections miss potential information spillovers across non-selected currencies. As shown in this paper, many spillovers arise among seemingly unrelated currencies. Second and related to the first point, previous papers generally examine a few currencies at a time. But the information spillover within the sample can be originated from a non-included currency. That is, the discovered spillover effect between two currencies is actually caused by a third currency not in the sample. To identify the sources of spillover, it is necessary to examine all relevant currencies because the origins are likely to be "sparse", in other words, only a few currencies are the sources of information spillover at a given time. Third, existing tests of information spillover are based on VAR-type models. The highly parameterized models are difficult to extend to a large number of currencies. Moreover, they may be misspecified. The constant structure is inconsistent with the evidence in this paper that the spillover effect is time-varying as the origin currencies change over time. Finally, the previously documented evidence of information spillover is in-sample. To firmly validate the existence of information spillover, it is critical to find out-of-sample evidence.

In this paper, we adopt the post Least Absolute Shrinkage and Selection Operator (post–LASSO) to identify and measure information spillovers across multiple currencies (e.g., Efron, Hastie, Johnstone, Tibshirani, et al. (2004); Meinshausen and Yu (2009); Belloni and Chernozhukov (2013)). Specifically, the post-LASSO forms the rolling 1–month–ahead currency excess return forecasts using other countries' lagged forward discounts as candidate predictors. Different from the VAR-type models, the parsimony of post–LASSO enables us to examine all important currencies simultaneously without pre-selection. The method is highly flexible and allows time-variation in the choices of predictors and coefficients. It is particularly powerful in capturing the sparsity of spillover origins. Most importantly, the post–LASSO generates a forecast of next-month return for each currency, denoted by SO_{it} for the i-th currency in month t. The forecasted returns can by applied for trading. A strategy of buying high-SO currencies and selling low-SO currencies yields an average monthly return of 1.05%. The profits of the strategy cannot be explained by existing currency strategies, and are robust even after controlling for currency momentum, carry trade, and return volatility.

The strong predictive power of SO is not totally surprising since LASSO-type estimators are known for superior out-of-sample performance than the standard regression models (e.g., Zou (2006); Zou and Hastie (2005)). As a penalized regression method, the post–LASSO imposes an l_1 penalty term and permits shrinkage to exactly zero for some coefficients. Consequently, it removes all but a few most relevant currencies, the origins of information spillovers. The sources of spillovers are therefore "chosen" by the data instead of researchers. Some of the origins are truly unexpected in the sense that they are not close to the affected currencies. For instance, Indonesian Rupiah is identified as an origin currency by the post–LASSO after the 97' Asian Financial Crisis for almost all global currencies beyond those in Southeast Asia.

To verify whether the post–LASSO correctly selects the origins of information spillovers, we conduct a validation test by examining the currencies selected by the post–LASSO. Specifically, we estimate regressions of the number of times a currency is selected as a predictor by the post–LASSO at time t on various independent variables. The test results reveal that the selected currencies tend to have experienced large movements, and have high forward premiums. In particular, some origin currencies have crashed recently. For instance, Indonesian Rupiah and Malaysian Ringgit are origins to many others during the three years after the 97' Asian Financial Crisis. Similarly, Russian Rouble and New Turkish are origins following their corresponding crises. In addition to crashed currencies, safe haven currencies are sometimes the origins of information spillovers. For example, Australia Dollar and Swiss Franc frequently entered the set of predictors selected by post–LASSO during the 2000s. The findings are consistent with the evidence for the important role of safe–haven currencies for global investors (e.g., Campbell, Serfaty-De Medeiros, and Viceira (2010); Ranaldo and Söderlind (2010)). In sum, the post–LASSO seems to capture the complexity of information spillovers in the FX market.

Given the significant return predictability of SO, it is critical to investigate whether higher returns are associated with higher risks. To test this, we estimate a regression of a country's uncertainty beta in month $t+1$ and its SO in month t. The evidence indicates that SO is positively related to a country's future uncertainty beta. Moreover, high-SO currencies have larger downside risk (e.g., Ang, Chen, and Xing (2006a); Chernov, Graveline, and Zviadadze (2018); Dobrynskaya (2014)). In addition, we find that the SO measure has a significant positive loading on the U.S. inflation factor of Ludvigson and Ng (2009). Since the U.S. inflation has a direct impact on other countries' inflation (e.g., Ciccarelli and Mojon (2010)), SO also captures the inflation risk. These test results support the risk explanation to the high returns of high-SO currencies.

A growing number of papers apply LASSO-type methods to finance research (e.g., Freyberger, Neuhierl, and Weber (2017); Chinco, Clark-Joseph, and Ye (2018b); Chinco, Neuhierl, and Weber (2018a); Bryzgalova (2014)). To the best of our knowledge, this paper is the first one to use the post-LASSO to study the FX market. It contributes to the information spillover literature in several ways. First, unlike previous papers which focus on a pre–determined small subset of currencies, this paper examines all currencies at the same time.

Second, the post–LASSO identifies the origins of information spillovers according to a set of statistical rules. The existing studies, however, use VAR-type models to test pre-imposed spillover relations. Third, our measure of spillover exposure SO has practical implications. It can be used to form profitable trading strategies. The positive relation between the cross-sectional future currency returns and SO has a risk explanation. This sheds lights on the forward premium puzzle. One reason that the forward exchange rate of a currency is a biased forecast of its own future spot rate is because the spot rate is also affected by the forward rates of other currencies through information spillovers.

Our article is organized as follows. Section 2 contains the literature review. Section 3 introduces the post–LASSO and describes the data. Section 4 discusses the empirical results. Section 5 concludes.

2 Literature Review

Our paper relates to mainly four strands of studies. Primarily, this paper is positioned in the literature of the inter-temporal information spillovers. This strand of literature documents the existence of inter-temporal information spillovers. Brandt, Cochrane, and Santa-Clara (2006) demonstrate a high international risk sharing "across several pairs of countries" by constructing an index of international risk sharing. Using three currencies – Japanese yen, British pound sterling, and Germany mark, Nucci (2003) finds that the term structures of forward premiums from other currencies can predict the currency's own spot rate changes even after controlling for the currencies' own term structure of forward premium. MacDonald and Marsh (2004) use the same set of three currencies and simultaneous models to explore the information spillover effect. Wang, Yang, Wang, and Fawson (2017) extends Nucci (2003) and MacDonald and Marsh (2004) by detecting the spillover effects for both non-deliverable forward and deliverable forward. Similarly, their study is restricted to predetermined regions, Northeast Asia, South/Southeast Asia, and Latin America. Other studies on the spillover effects in sovereign debt market (Gande and Parsley (2005)) and international stock market (Phylaktis and Ravazzolo (2005)) are also based on predetermined pairs.

The common limitation among these studies is these studies can only manage to explore spillovers within a small subset of currencies. Using these predetermined pairs, the studies cannot be immunized from the critique of tautology: selectively choosing the pairs of currencies (such as the ones in the same region) most likely to co-move and test their information spillovers. Even more severely, the information spillovers are definitely not restricted to the chosen pairs (within the same region). During the 2000s, a significant amount of currencies loads on safe haven currencies such as Australian dollar and Swiss Franc. For instance, based on our empirical tests, Brazilian real, Indonesian Rupiah, Mexican Peso, and Russian Rouble are all exposed to the Swiss Franc. None of these countries are in the same region of Swiss. By the same token, in Year 2017, Egypt and Russian Rouble have impact on other currencies far beyond the region they belong to.

The currencies as the origin of information spillovers vary by time and are not constrained by regions. Moreover, the key currencies that have wide impact on other currencies are relatively rare (sparse) for each time period. The prior literature is insufficient to model the complex nature of the information spillovers. In contrast, our post–LASSO framework can simultaneously incorporate the nature of time variation and sparsity in identifying the origins of information spillovers and estimating the heterogeneous exposures of other currencies.

Our work also relates to the studies on downside risk/crash risk in currency markets. These studies employ different measures to show that downside risk (Dobrynskaya (2014)) and crash risk (Chernov, Graveline, and Zviadadze (2018)) are priced in the cross section of currency returns. Downside risk also matters for the performance of carry trade (e.g., Lee and Wang (2018); Burnside, Eichenbaum, Kleshchelski, and Rebelo (2010); and Brunnermeier, Nagel, and Pedersen (2008)). Our paper extends the prior studies by showing that the crash spillover is in the information content of our information spillover measure and therefore matters for currency returns.

Thirdly, our paper also links to research on the forward premium puzzle. The excess return of carry trade has been extensively specified as risk premiums related to this forward premium puzzle. Prior research finds that the profit from carry trade is related to peso problem (Burnside, Eichenbaum, Kleshchelski, and Rebelo (2010)), crash risk (Lee and Wang (2018)), consumption risk (Lustig and Verdelhan (2007)), market liquidity (Acharya and Steffen (2015) and Brunnermeier and Pedersen (2008)), and speculative positions (Garleanu and Pedersen (2011)). Our paper explore the forward premium puzzle from the other side: the currency's own forward rate is a biased forecast of future spot rate change because the future spot rate dynamics contains a premium of information spillover.

Last but not least, this study has a natural relation with papers applying the technique of LASSO and post–LASSO to finance data. Prior studies employ LASSO type of methods to identify factors providing independent information in the cross section (Freyberger, Neuhierl, and Weber (2017) and Feng, Giglio, and Xiu (2017)), to enhance portfolio optimization (DeMiguel, Garlappi, Nogales, and Uppal (2009)), and to design new model–specification tests (Chinco, Neuhierl, and Weber (2018a); Bryzgalova (2014)). The most relevant paper to our study is Chinco, Clark-Joseph, and Ye (2018b). They use LASSO to shrink the large cross section of stocks used as the candidate factors and get sparse signals to predict future one–minute stock returns. Our study differs from Chinco, Clark-Joseph, and Ye (2018b) on several grounds. First, our battlefield is on currency market which has long been documented to be inter–connected. Currency market has a relatively small cross section than that of stocks. Therefore, it is more intuitive to justify the economic intuition of the LASSO selection. More importantly, our study has significant implications on the forward premium puzzle, implying that the pricing kernel for currency returns should incorporate the inter-temporal spillovers from other currencies. Additionally, our findings indicate that even at monthly frequency, the spillover effects on the currency market are still pronounced.

3 Data and the Empirical Design

This section aims to explain the basic principle of LASSO and post–LASSO methods and their implementation in our research. The data feeding to our post–LASSO model covers the period from January 1993 to June 2018 at a monthly frequency. Our sample consists of 48 currencies including Australia dollar, Austrian Schil, Belgian Franc, Brazilian Real, Bulgarian LEV, Canadian dollar, Chinese Yuan, Czech Koruna, Danish Krone, Netherland Guilder, Egyptian Pound, Euro, Finnish Markka, French Franc, German Mark, Greek Drachma, HongKong dollar, Hungarian HUF, Indian Rupee, Indonesian Rupiah, Israeli Shekel, Italian Lira, Japanese Yen, Kenyan Schilling, Kuwaiti Dinar, Mexican Peso, Malasian Ringgit, Moroccan Dirham, Norwegian Krone, New Zealand dollar, Philippine Piso, Polish Zloty, Pakistani Rupee, Portuguese Escudo, South Africa, Russian Rouble, South Korean, Swiss Franc, Singapore dollar, Swedish Krona, Saudi Riyal, New Romanian, Spanish Peseta, New Turkish, Taiwan new dollar, Thai Baht, and UK Pound.

Our sample is largely coincident with the samples in prior studies such as Menkhoff, Sarno, Schmeling, and Schrimpf (2012b) and Menkhoff, Sarno, Schmeling, and Schrimpf (2012a). We further split our sample into developed and emerging countries based on the classification in Menkhoff, Sarno, Schmeling, and Schrimpf (2012b). The list of developed countries includes: Austrian Schil, Australia dollar, Belgian Franc, Canadian dollar, Danish Krone, Euro, Finnish Markka, French Franc, German Mark, Netherland Guilder, Norwegian Krone, New Zealand dollar, Italian Lira, Portuguese Escudo, South Africa, Japanese Yen, South Korean, Swiss Franc, Singapore dollar, Swedish Krona, and UK Pound. The rest of the countries are left to the sample of developing countries.

One caveat of our sample is that the effective sample size varies over time as the inclusion and exclusion of currencies. For instance, after the Year 2002, eight currencies including Austrian Schil, Belgian Franc, Netherland Guilder, French Franc, German Mark, Greek Drachma, Italian Lira, Spanish Peseta are replaced by Euro. We set the observations on these eight currencies to be NaN after Year 2002. The variation in the sample size cannot affect our results since the estimation of our spillover measure does not rely on the sample size and our main analytical tool is via portfolio sorts.

I adopt the perspective of a U.S. investor and collect for each country the spot rate and 1–month forward exchange rate against U.S. dollar from Datastrem. An increase in spot or forward rates indicates an appreciation against U.S. dollar. We employ the samples of spot rate and 1–month forward rate to construct currency excess return and the forward discount. Specifically, the monthly excess return to a U.S. investor for holding currency i is given by:

$$rx_{i,t+1} = f_{i,t} - s_{i,t+1}, \tag{1}$$

where s and f denote the (log) spot and one–month forward rate, respectively. Following prior literature, we define the forward discount as the difference between current spot rate and forward rate $f_{i,t} - s_{i,t}$.

3.1 The Empirical Design

Our predictive framework can be summarized by the following two–stage procedure. First, we run a regression of the i's currency excess return in month $t+1$ on lagged forward discount of all other currencies excluding the i's as shown in the following equation:

$$rx_{i,t+1} = \alpha_i + \sum_{i*=1(i*\neq i)}^{N} \beta_{i,i*}(f_{i*t} - s_{i*,t}) + \epsilon_{i,t+1}, \tag{2}$$

where $rx_{i,t+1}$ is the currency excess return of currency i at time $t+1$; $\sum_{i*=1(i*\neq i)}^{N} \beta_{i,i*}(f_{i*t} - S_{i*,t})$ stands for the whole cross section of forward discounts except the one from currency i. Equation 2 allows for all lagged forward discount in the regression. That is, if we have a sample of 48 countries in the cross section, there will be 47 forward discounts as the candidate predictors. The number of information spillover origins is far fewer than 47 at each periods. The high dimension nature (N = 47) posts a problem for the conventional OLS regression.

Using OLS regressions for the above equation leads to a paradox of sample size selection. To accurately estimate the predictive power of each candidate predictor for this high–dimensional data, we need a much longer sample. However, longer sample period for estimation can average out the shocks from the origins of spillovers and lead to mis-specification, given the time–varying nature of the information spillover origins. For instance, Malaysian Ringgit is one of the origin of the information spillover in the following three years after the Asian Financial Crisis. We need to at least a sample of 48 months to estimate the coefficients. To mitigate the concern of over–fitting in OLS, we may enlarge the sample to 204 months. Therefore, the three–year sample of Malaysian Ringgit as the origin (post Asian Financial Crisis) is buried in the longer sample of 204 months (17 years). Increasing the sample size definitely leads to the underestimation of the impact of Malaysian Ringgit.

To solve the paradox, we employ LASSO for the predictor selection. Tibshirani (1996) introduces the penalized regression method LASSO to shrink the large cross section of candidate predictors. The objective function for Equation 2 via LASSO can be expressed as:

$$\widehat{\alpha_n}, \widehat{\beta_n} = argmin\left\{ \frac{1}{L} \sum_{l=0}^{L-1} \left(rx_{i,t-l} - \alpha_n - \sum_{i*=1}^{N} \beta_{i,i*}(f-s)_{i*,t-(l+1)} \right)^2 + \lambda_n \sum_{i*=1}^{N} 1_{\beta_{i,i*\neq 0}} \right\}, \quad (3)$$

where $\widehat{\beta_n}$ is the 47×1 dimensional vector of coefficients used to forecast the excess returns of the i's currency. The first component in the parentheses in Equation 3 is the sum of square errors used in the conventional OLS. The second term $\lambda_n \sum_{i*=1}^{N} 1_{\beta_{i,i*\neq 0}}$ is the l_1 penalty term which can shrink the large cross section of coefficients. If λ_n equals zero, the LASSO estimator degenerates to OLS estimator. Otherwise, LASSO yields different estimates for the regression coefficients and penalizes certain coefficients to zeros.

LASSO performs well in feature selection against OLS (e.g., Zhang, Huang, et al. (2008)). However, LASSO estimators suffer from downward bias (Fan and Li (2001)). In other words, LASSO over–penalizes the coefficients so that the effects of the most relevant predictors are underestimated. To overcome the problem of biased estimation, we re–estimate the coefficients for the LASSO–selected predictors via OLS following prior literature in statistics such as Efron, Hastie, Johnstone, Tibshirani, et al. (2004) and Belloni and Chernozhukov (2013).

Therefore, for each rolling N periods, our information spillover measure can be estimated via OLS post–LASSO procedure as follows:

- First, we standardize the independent variables– forward discounts by max–min standardization. Careful standardization can lead to fast converge of LASSO method (Nasrabadi (2007)).

- Second, we run a LASSO regression of currency excess return on all other countries' forward discounts and save the most relevant forward discounts selected by LASSO. The penalty coefficient is determined through careful grid search.

- Finally, we re–estimate the coefficients through OLS regression of excess returns on LASSO–selected predictors. The estimated value from the regression is our measure of information spillover.

More specifically, we set the training periods to be $N = 50$. The size of the training sample is hard for OLS to make inference due to the high dimension of the data (48 countries) but enough for our OLS post–LASSO methods. The reason is that after the LASSO regression in the first stage, on average four predictors are left for the OLS regression in the second round. We perform the OLS post–LASSO regressions of currency excess returns in time $t+1$ on all other countries' forward discounts in time t to get the predicted values of excess returns in time $t+1$. The predicted values SO_{it} in period $t+1$ are then used as the measures of degree of information spillovers to predict the future currency excess returns in period $t+2$.

3.2 In–Sample Validation Tests

Before approaching to the return predictability of SO_{it}, we provide two sets of validation tests to further understand the information content of SO_{it}. We first validate our OLS post–LASSO procedure by manually sampling periods with countries in financial crisis. The countries in financial crisis can definitely have spillover effects on other relevant countries. We expect our OLS post–LASSO method to accurately identify the currencies in the crisis and sufficiently estimate the heterogeneous loadings of other currencies on the information origins. A natural playfield is the post 97' Asian Financial Crisis period. We manually look into the 12 months in Year 2001 to document the most relevant predictors selected by LASSO. The reason we choose the Year 2001 is that our 50-month training sample covers the period from Year 1998 to 2001, during which currencies in the crisis have wide impact to the other currencies.

Table 1 reports the relevant predictors selected by LASSO in December 2001. We list the 48 currencies in the column and selected predictors by LASSO in the each row. We can find that, in total, only 12 countries' forward discounts are selected as the most relevant predictors suggested by LASSO for excess returns of all currencies. Several interesting patterns arise. First, the results confirm our conjecture that only a handful of other countries' forward discounts are determinants of one country's future excess returns. The maximum number of relevant predictors arises from the prediction of New Turkish: six relevant predictors including Brazilian Real, Australia dollar, Indonesian Rupiah, Malaysian Ringgit, Mexico, and South Africa. Most of the currencies' excess returns are predicted by three to four forward discounts from other currencies.

Second, among these 12 predictors, currencies in the Aisan Financial crisis such as Indonesian Rupiah and Malaysian Ringgit have compelling impact on currency excess returns of almost all other countries. Thai Baht, which is also trapped in the crisis, has impact on three currencies, Australian dollar. In other words, LASSO succeeds in identifying the currencies in the crisis as the most relevant predictors.

Moreover, Brazilian Real, South Africa, and New Turkish are also identified as the key predictors. A key–word search through Lexus–Nexus on these three currencies during the same period indicates they are origins of spillovers. Brazilian Real experienced a significant appreciation in the Year 1999. Therefore, in this time period, the crash spillover is the main information content of SO_{it}. More importantly, the results indicate that LASSO regression can identify the most relevant predictors in the system.

Thirdly, the relevant predictors selected by LASSO indicate weak evidence of information spillovers among currencies in the same region. For instance, we find no information spillovers among currencies in Northeast Asia (China, Korea, Taiwan). Evidence indicates that one of the relevant currency for the Indian Rupee is Malaysian Ringgit. However, one cannot identify this as the exact evidence of information spillovers in South/Southeast Asia given the global impact of Malaysian Ringgit during the Asian Financial Crisis. Our findings do not go against the existence of the regional information spillover. But the findings in Table 1 do imply that the global information spillovers but not spillovers among certain regions are of the first–order importance. Prior studies intra-regional information spillovers highly likely miss the full picture.

To further confirm the advantage of LASSO in capturing the global information spillovers, we turn to the next crisis period, the 08' global financial crisis. We look at the relevant predictors selected by LASSO in the Year 2011 which fully covers the financial crisis period. Table 2 reports the relevant predictors selected by LASSO. Consistent with prior findings in Table 1, only 13 countries in total are identified as the most relevant predictors. Similarly, most of the currencies have three to five key predictors. The maximum number of relevant predictors is six, for the excess returns of Australian dollar.

The patterns in Table 2 show significant differences from that in Table 1. First, the relevant predictors with the highest frequency selected by LASSO are Australian dollar, Egypt, Swiss, South Korea, Russian Rouble. Indonesian Rupiah and Malaysian Ringgit disappear from the list of selected relevant predictors, indicating that our OLS post–LASSO procedure captures the time–varying nature of the information–spillover origins.

Second, the selected predictors with high frequencies are not just the ones in severe crisis but can be separated into two groups. Egypt, South Korea, and Russian Rouble are currencies in severe crisis. This finding further confirms the results in Table 1 that countries in crisis can be identified as relevant predictors. In addition to the crash currencies, Australian dollar and Swiss Franc are also identified as key predictors with high frequency. These two currencies are identified as the safe haven currencies moving against world equity markets (e.g., Campbell, Serfaty-De Medeiros, and Viceira (2010)). Our findings are consistent with Campbell, Serfaty-De Medeiros, and Viceira (2010) that the Swiss Franc goes against global equity market "particularly in the second half of the period" from the Year 1975 to 2005. Our findings augment the literature on the safe haven currencies by showing that not all currencies with the safe haven property have spillover effects on other currencies. To sum up, Table 2 enriches the information content of our information spillover measure SO_{it} by showing that currencies in crashes and the ones with the property of safe haven can both act as the origins of information spillovers.

We also explore the relevant predictors selected by LASSO in the more recent sample periods. Table 3 reports the LASSO–selected relevant predictors in the December 2017. In this era, the impact of safe haven currencies on the rest of currencies disappears. Russian Rouble and Eygptian currency are the most relevant predictors.

We cannot deplete all rounds of LASSO selection to justify the advantage of our OLS post–LASSO methods. Instead, we translate the intuition from Table 1 to Table 3 by Fama–MacBeth regressions of the number of selections for each currency at each period on carefully selected independent variables. The dependent variable is the number of selections by LASSO for currency i at period $t + 1$. The independent variables are the change in spot rate, the forward discount, and excess return in period t. Changes in the spot rates measure the state of currency appreciation/depreciation. The forward discounts measure the premium of expected rate against realized rate. Table 1 to Table 3 indicate that the frequency of selections for currency i increases in the degree of crisis. Therefore, we expect a positive relation between the number of selection and the lagged changes in spot rates since a large decrease in spot rates means a higher degree of downside risk, that is, a sharp depreciation of the respective currency against the U.S. dollar. We also include measures the positive jumps and crash in spot rates and forward discounts.

Table 4 reports the corresponding average coefficients of the Fama–MacBeth regressions. Consistent with our conjecture, the lagged changes in spot rates have a positive relation with the number of selections in the future. The magnitude of the coefficient on ΔS_t is large. A 1% increase in the spot rate leads to 1.17 times more selections. A crash of 10% depreciation leads to 11.7 times' more selection. The forward discount also shows a positive relation with the number of selection in the future. a 1% increase in the forward discount leads to 1.67 times more selections, indicating that the expected depreciation in currencies lead to more selections. In untabulated results, we find financial crisis dummy based on the crash identification in Dobrynskaya (2014) and Ranaldo and Söderlind (2010) has a positive relation with the number of selection. Safe haven dummies also have a significant but weaker positive relation. The reason for the weaker condition of safe haven dummies is that safe haven currencies as the relevant predictors are only pronounced in the 2000s. To sum up, both manual search and regressions analysis indicate that the OLS post–LASSO predictors succeed in incorporating the information spillovers from other currencies.

Even though our OLS post–LASSO procedure correctly identifies the origins of information spillovers, can it accurately estimate the loadings of currency excess returns on the forward discounts of the information origins? If yes, our information spillover measure SO_{it} must be priced in the currency markets. We examine the return predictive power of SO_{it} in the next section.

4 Empirical Results

To detect the return–predictive power of SO_{it}, we rely mostly on the portfolio sorts and cross–sectional regressions of Fama and MacBeth (1973) with Newey and West (1987) for our empirical investigation.

4.1 Econometric Methods

First, we employ the single portfolio sorts to examine the impact of SO_{it} on excess returns. At the end of each month, we form quintile portfolios based on the magnitude of SO_{it} and then consider the equal–weighted portfolios' currency excess returns. Specifically, the one–fifth of all available currencies in a given month that have lowest SO_{it}s are allocated to the first portfolio (denoted as "weak"), the next fifth is allocated to portfolio 2 and so on, and the one–fifth of all currencies with the highest SO_{it} are allocated to the fifth portfolio (donoted as "strong"). If our information spillover measure SO_{it} is positively related to currency excess returns, we expect an increasing pattern of portfolio returns from quintile 1 to quintile 5.

To detect whether SO_{it} has independent information against other currency excess return predictors, we employ double portfolio sorts and the Fama–MacBeth regressions. To perform the double portfolio sorts, we first rank currencies into Quartiles by a control variable such as currency momentum and forward discount and then further sort currencies within each portfolio into quartiles by SO_{it}. If the control variable can explain the predictability of SO_{it}, we expect the increasing pattern of excess returns in SO_{it} to be much less significant in each quartile of the control variable. To compute t-statistics of average portfolio returns, we use Newey and West (1987) adjusted standard errors because of the persistence in the portfolio compositions[1].

For the Fama and MacBeth regressions, we expected the average estimated coefficient of SO_{it} to be positive and significant. The cross–sectional regressions allow us to examine the marginal effect of the SO_{it} when controlling for other variables known to predict currency excess returns. In the most general specification, we include forward discount and currency momentum as the control variables in the regression. If SO_{it} captures information about currency excess returns beyond that in other variables, the coefficient of the SO_{it} should be significant even in the presence of all control variables.

[1] We use six lags to adjust the standard error. Using more lags does not change the results.

4.2 Summary Statistics of SO_{it}

One may concern that a fixed group of currencies is inclined to be affected by information from other currencies. In other words, we need to mitigate the concern that some currencies have extreme values in SO_{it} and enter the two extreme portfolios all the time. To justify that our high and low SO_{it} portfolios are not dominated by certain currencies, we step back to report the summary statistics of SO_{it}. Table 5 report for each currency the time–series mean, median, standard deviation, 25th percentile, 75th percentile, MIN, and MAX of SO_{it}. We find the mean and median of SO_{it} for each currency are all around 0.5. The standard deviations of SO_{it} across currencies are of the same scale, from 0.23 to 0.31. The other percentile statistics of currencies is also of the same scale. The reason can be attributed to the min–max standardization we did before inputting variables into LASSO regressions. In general, the summary statistics largely eliminates potential critique.

4.3 Single Portfolio Sorts

Table 6, Panel A, shows the average monthly excess returns for decile portfolios sorted by SO_{it} for our full sample. We also report the return difference of the two extreme portfolios and call it the "SMW". The average monthly excess return of longing the strong portfolio and selling short the weak portfolio is 1.051%, which is statistically significant at 1% level. The profit of SMW is not solely driven by either the long side or the short side. The monthly excess return of the Strong portfolio (0.508%) and that of the weak portfolio (-0.543%) are similar in absolute values. To examine the stability of the strategy, we also report the 25th and 75th percentiles of portfolio returns. The 25th (75th) percentile of the strong portfolio is -0.55% (1.03%) and that of the weak portfolio is -1.66% (1.85%), indicating that the return spread of SMW is driven by smooth accumulation of stable returns monthly rather than large return spread in few months. This indication is confirmed by Figure 3. The monotonic increasing excess returns from weak to strong portfolios indicate a high information coefficient.

Table 6, Panel B and Panel C, report the results of single portfolio sorts for developing and developed countries. The SMW is more pronounced in the sample of developing countries. Specifically, the SMW is 1.79% per month in developing countries but 0.54% per month in developed countries. Moreover, the strategy based on SO_{it} is not profitable when market state is good since the monthly return of strong (weak) portfolio in 75th percentile is 1.52% (1.58%). In other words, the difference of SMW in developing and developed samples indicates that the information spillover effect is stronger in developed countries.

4.4 Comparing SMW with Other Factors

An important question is to what extent our information spillover strategies capture the same information as other risk factors in currency markets such as carry trade and currency momentum. One can argue that if information travels fast enough, one country's forward discount can incorporate the shocks from other countries sufficiently quick. Therefore, knowing the measure of information spillover provides no additional information against the own country's forward discount.

4.4.1 Portfolio Return Correlations

Once determining the return predictive power of SO_{it}, we design additional tests to detect whether SO_{it} provides independent information against other return predictors. We first explore the correlation of SMW factor with Lustig, Roussanov, and Verdelhan (2011) common factors and also the Fama and French (2016) five factors. Table 7, Panel A shows correlation coefficients between returns to each SO_{it}–quintile portfolios and other risk factors. There is an increasing correlations of RX factor and SO_{it} quintile portfolios (from Weak to Strong). The correlation between RX and Weak (strong) SO_{it} portfolio is 0.08 (0.17). However, the correlation between the SMW and RX is quite low at 0.04. SMW has a relatively high correlation with Lustig's slope factor HML_{Lustig} of 0.13 for the full sample. As for the Fama–French five factors, the correlations are all below 0.24. Therefore, the SO_{it}

portfolio SMW provides quite independent return pattern against traditional risk factors. Our findings is further convinced in the two subsamples output in the Panels B and C.

Low correlations with conventional factors cannot guarantee significant factor–adjusted returns. The conventional factors may capture the component of SO_{it} most related to future returns. To address this concern, we perform time–series regressions of monthly SMW on multiple factors. Table 8 reports the corresponding results for Weak, Quintile 3, Strong, and SMW portfolios. There are several interesting patterns worthwhile to discuss. First, SMW has a significant positive monthly factor–adjusted returns around 1.20% even after controlling for different combinations of conventional factors. This is due to the significant positive (negative) abnormal return of the Strong (Weak) portfolio. Second, even though Fama–French factors have a relatively high correlation (comparing with Lustig's common factors) with SMW, they can hardly explain the return pattern of SMW. The high correlations between Fama–French factors and SMW may be largely due to the fact that we use U.S. dollar as the numeraire for exchange rates. Third, Lustig's factors have significant loadings on our SMW factor but cannot explain the dynamics of SMW.

4.4.2 Double Portfolio Sorts

We perform sequential portfolio sorts to examine the marginal return predictive power of SO_{it} against currency momentum and carry trade. Table 9 reports the corresponding results. Panel A and Panel B report the sorts controlling for currency momentum and carry trade, respectively.

Panel A indicates that the monthly average return of strong minus weak portfolios controlling for momentum is 0.595% ($1.40\% + 0.16\% - 0.16\% + 0.98\%$). Comparing with the unconditional SMW of 1.051%, controlling for momentum eliminate 40% of SMW's return spread. However, the average return of 0.595% controlling for momentum is still significant at 1% level, implying that the effect of SO_{it} is still significant even controlling for the effect of currency momentum. When looking into the SMW across each momentum quartile, we find that the SMW is large in the extreme momentum portfolios but disappear in mid portfolios. This is not surprising because currencies with large appreciation/depreciation tend to be selected as the relevant predictors incorporated into the information content of SO_{it}. Panel B reveals that the monthly average return of SMW across carry trade quartiles is 0.73% and significant at 1% level. Similar to the findings in Panel A, the SMW return spreads are large in the extreme carry trade portfolios but weak in the mid portfolios.

Panel C and Panel D are sorts for developing countries. Panels E and F are for developed countries. We come to the same conclusions using these two subsamples: (i). SMW conditional on the momentum and carry trade is significant at 1%; (ii). SMWs are large in the extreme portfolios.

4.4.3 Fama–MacBeth Regressions

Sequential portfolio sorts can only include one control variable in the sorts. To estimate the return predictability under the joint effect of momentum and carry trade, we run Fama–MacBeth type cross–sectional regressions of currency excess returns on (i). SO_{it}; (ii). lagged currency excess returns; (iii). forward discount for each month of our sample, i.e.,

$$Rx_{i,t+1} = \alpha_t + \beta_{Rx,t} Rx_{i,t} + \beta_{FD}(f_t - S_t) + \beta_{\Delta S,t} \Delta S_{i,t} + \epsilon_t \tag{4}$$

Table 10 shows results for regressions where we use SO_{it}, lagged currency returns, and forward discount as explanatory variables. Panel A is for the fullsample. Panels B and C are for subsamples of developing and developed countries. Turning to the results, we find that, in univariate regressions (Models (1)–(3)), SO_{it}, lagged currency returns, and forward discount are cross-sectionally positively related to subsequent currency excess returns. Moreover, Models (4)–(6) are pairwise regressions of the three variables. The results show that the return predictive power of SO_{it} and lagged currency returns (forward discount) either dominate or absorb each other in the full sample. Model (7) includes all three variables and finds that the return predictive power of lagged excess returns is largely mitigated.

The regressions in the two subsamples yield slightly different results. First, consistent with portfolio sorts for subsamples, the return predictive power of SO_{it} is large in developing countries. For the sample of developed countries, simultaneously including SO_{it}, lagged currency returns, and forward discount in the regression makes the coefficients on SO_{it} only marginally significant. Moreover, in each subsample, we find the return predictability of SO_{it} dominates that of lagged currency returns, indicating that the information spillover effect absorbs that of currency momentum. The weak performance of currency momentum in subsamples may be attributed to several reasons. The first reason is the size cross section of each subsamples. In each subsample, the size is only around 22 which can significantly reduce the performance of currency momentum (Menkhoff, Sarno, Schmeling, and Schrimpf (2012b). The second reason can be due to a potential momentum crash in recent years. To sum up, we find that SO_{it} is a significant return predictor even controlling for the effect of currency momentum and carry trade. The performance of SO_{it} is stable across different subsamples.

4.5 Understanding the Mechanism

Does the profit of SO_{it} come from bearing risk or from the limit to arbitrage? We strive to understand the sources of return predictive power of SO_{it} from two aspects. First, we explore whether macroeconomic dynamics relate to the performance of SO_{it} portfolio returns. If SMW loads on common macro factors, SMW tends to be a risk premium for bearing macro risk. Second, we examine whether SO_{it} indicates a higher future uncertainty. If SO_{it} can predict future uncertainty, investors who are bearing SO_{it} need compensation for the risk.

We test the relation between macro factors and SMW by running regressions of SMW on the lagged common macro factors in Ludvigson and Ng (2009). Ludvigson and Ng (2009) employ dynamic factor analysis to extract the common variation of 132 measures of the U.S. economic activity. They provide nine factors, F1 through F8, and the cubic of F1. F1 is interpreted as the real factor capturing activity of employment and production. F2 has a high loading on the *Baa*–Fed fund rate spread. The third and fourth factors, F3 and F4, relate to the U.S. inflation. F8 is highly correlated with U.S. stock markets.

Table 11 reports the regression results of SMW in period $t+1$ on macro factors. The results indicate that F2, the interest rate factor, has a marginal loading on SMW. Moreover, F3 and F4, the inflation factors, have a strong impact on the performance of SMW. The other macro factors have negligible influence on SMW. The findings are not surprising since U.S. interest rate and inflation changes have a cascade effect on other currencies' forward discount (interest rate differential) and currency excess returns. SMW's loadings on inflation and interest rate indicate that the U.S. inflation and interest rate risk matter for the performance of SMW.

Next, we explore whether SO_{it} is directly related to currency–level risk measures. Following Ang, Hodrick, Xing, and Zhang (2006b) and Ang, Chen, and Xing (2006a), we calculate uncertainty beta as the monthly currency loadings on innovation of U.S. index option's implied volatility. We find that higher SO_{it} is associated with higher future uncertainty beta. Therefore, the premium associated with SO_{it} is a compensation for investors to bear higher future uncertainty.

5 Concluding Remarks

This study finds that the origins of inter–temporal spillovers in currency markets are sparse and time–varying in each period. Using predetermined region or pairs of countries cannot capture the full picture of the spillovers. From the in–sample validation tests, we find that our OLS post–LASSO framework can identify the rich dynamics of time–varying origins of information spillovers. The origins are mainly currencies in crisis and safe haven currencies.

We confirm that our framework can also accurately estimate other countries' heterogeneous loadings on the origins by showing that an information spillover measure SO_{it} based on OLS post–LASSO framework has a positive relation with future excess returns. In other words, we employ the Post–Least Absolute Shrinkage and Selection Operator (LASSO) to make rolling 1–month–ahead currency excess return forecasts using all countries' lagged forward discount as candidate predictors. A trading strategy by buying (selling) quintile portfolios of high (low) post–LASSO fitted values yields a monthly currency excess return of 1.05%. The return predictive power of SO_{it} is more pronounced in the emerging countries with a monthy return spread of 1.79%.

Our further evidence indicates a risk–based story for SO_{it}. We find that macro factors such as U.S. inflation and interest rate relate to the porfolio returns of SO_{it}. Moreover, a higher value of SO_{it} indicates a higher future uncertainty beta.

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Table 1: LASSO Selections Post 97' Financial Crisis Periods

This table reports the snapshot of the LASSO selection of most relevant forward discount from the most relevant countries in December 2001. The LASSO model are trained using previous 50 periods including December 2001. The column "currencies" is the dependent variable–currency excess returns in period $t+1$. The regressors are selected from the complete set of lagged currency forward discount of other countries in the first row. "***" indicates a selection, else not selected by LASSO.

Currencies	Australia	Brazilian	Japanese	Mexico	Indonesian	Malasian	New Zealand	Polish	South Africa	Swiss	Turkish	Thai
Australian $					***	***			***		***	***
Austrian Schil					***	***					***	
Belgian Franc					***	***					***	
Brazilian Real					***	***		***	***		***	***
Bulgarian LEV												
Canadian $		***			***	***					***	
Chinese Yuan												
Czech Koruna		***			***	***			***			
Danish Krone					***	***			***		***	
Neth. Guilder					***	***					***	
Egyptian Pound												
Euro					***	***						
Finnish Markka					***	***						
French Franc												
German Mark												
Greek Drachma												
HongKong $												
Hungarian HUF		***			***	***	***		***			
Indian Rupee						***					***	
Indonesian Rupiah												
Israeli Shekel												
Italian Lira												
Japanese Yen					***	***			***		***	
Kenyan Schilling												
Kuwaiti Dinar					***	***						
Mexican Peso					***	***					***	
Malasian Ringgit					***						***	
Moroccan Dirham												
Norwegian Krone		***			***	***			***		***	
New Zealand $		***	***		***	***			***		***	***
Philippine Piso		***			***	***					***	
Polish Zloty					***	***					***	
Pakistani Rupee												
Portuguese Escudo					***	***						
South Africa		***		***	***	***				***		
Russian Rouble												
South Korean					***	***			***			
Swiss Franc					***	***					***	
Singarpore $						***						
Swedish Krona		***			***	***			***		***	
Saudi Riyal						***						
New Romanian												
Spanish Peseta					***	***					***	
Slovenian Tolar		***										
New Turkish	***	***		***	***	***			***			
Taiwarn new $		***				***					***	
Thai Baht		***									***	
UK Pound					***	***					***	

Table 2: LASSO Selections Post 08' Financial Crisis Periods

This table reports the snapshot of the LASSO selection of most relevant forward discount from the most relevant countries in December 2011. The LASSO model are trained using previous 50 periods including December 2001. The column "currencies" is the dependent variable–currency excess returns in period $t+1$. The regressors are selected from the complete set of lagged currency forward discount of other countries in the first row. "***" indicates a selection, else not selected by LASSO.

Currencies	Australian	Brazilian	Czech	Egyptian	Indonesian	Kenyan	Kuwaiti	South Korean	Swiss	South Africa	Polish	Russian	New Zealand
Australian $		***		***		***	***	***	***				
Austrian Schil													
Belgian Franc													
Brazilian Real				***		***			***		***	***	
Bulgarian LEV	***						***	***				***	
Canadian $							***		***	***		***	
Chinese Yuan													
Czech Koruna				***					***	***			***
Danish Krone	***						***	***	***				
Neth. Guilder													
Egyptian Pound													
Euro	***						***	***				***	
Finnish Markka	***						***	***				***	
French Franc													
German Mark													
Greek Drachma													
HongKong $													
Hungarian HUF	***	***		***									
Indian Rupee				***		***							
Indonesian Rupiah				***			***	***		***	***		
Israeli Shekel				***				***	***				
Italian Lira													
Japanese Yen						***		***	***				
Kenyan Schilling													
Kuwaiti Dinar													
Mexican Peso				***					***			***	
Malasian Ringgit								***					
Moroccan Dirham													
Norwegian Krone				***			***	***	***				
New Zealand $	***		***	***				***	***				
Philippine Piso													
Polish Zloty													
Pakistani Rupee													
Portuguese Escudo	***						***		***			***	
South Africa		***		***					***			***	
Russian Rouble				***			***	***	***				
South Korean				***	***		***		***	***			
Swiss Franc	***						***	***				***	
Singarpore $								***					
Swedish Krona	***			***			***	***	***	***			
Saudi Riyal							***	***	***				***
New Romanian	***												
Spanish Peseta													
Slovenian Tolar	***						***	***				***	
New Turkish				***				***				***	
Taiwarn new $								***				***	
Thai Baht													
UK Pound	***							***				***	

Table 3: LASSO Selections in 2017

This table reports the snapshot of the LASSO selection of most relevant forward discount from the most relevant countries in December 2017. The LASSO model are trained using previous 50 periods including December 2001. The column “currencies” is the dependent variable–currency excess returns in period $t+1$. The regressors are selected from the complete set of lagged currency forward discount of other countries in the first row. “***” indicates a selection, else not selected by LASSO.

Currencies	Czech	Euro	Eygpt	Indonesian	Japanese	Russian	South Africa	South Korea	New Zealand	Swiss
Australian $			***							
Austrian Schil										
Belgian Franc										
Brazilian Real	***	***	***			***				
Bulgarian LEV			***			***				
Canadian $			***			***		***		
Chinese Yuan			***							
Czech Koruna			***							
Danish Krone			***			***				
Neth. Guilder										
Egyptian Pound				***				***	***	
Euro			***			***				
Finnish Markka			***			***				
French Franc										
German Mark										
Greek Drachma										
HongKong $										
Hungarian HUF			***							
Indian Rupee			***							
Indonesian Rupiah			***							
Israeli Shekel			***							
Italian Lira										
Japanese Yen			***					***		
Kenyan Schilling			***							
Kuwaiti Dinar			***							
Mexican Peso			***							
Malasian Ringgit			***							
Moroccan Dirham			***							
Norwegian Krone			***							
New Zealand $								***		
Philippine Piso			***							
Polish Zloty			***							
Pakistani Rupee										
Portuguese Escudo			***			***				
South Africa	***		***		***					
Russian Rouble			***				***			***
South Korean			***							
Swiss Franc			***							
Singarpore $			***							
Swedish Krona			***							
Saudi Riyal										
New Romanian			***			***				
Spanish Peseta			***			***				
Slovenian Tolar			***			***				
New Turkish			***				***			
Taiwarn new $										
Thai Baht			***							
UK Pound			***							

Table 4: The Determinants of Number of Selections

Each column reports the results of a different Fama–MacBeth regression. We report the average coefficient of all periods. The dependent variable is the number of times that the i'th stock was selected in period t. The independent variables are lagged spot rate changes, excess returns, forward discount, and the jump and crash in spot rates. We report the corresponding t statistics in the brackets. The Newey–West standard errors are employed to adjust the t statistics. ***, **, and ** represent significance at 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta Spot$	117.49***						103.77***
	[10.28]						[4.30]
Excess Return		0.23			-1.06	3.18	-1.31
		[0.04]			[-0.17]	[0.52]	[-0.16]
Fwd Discount		167.35***			195.68***	130.84***	138.17***
		[9.06]			[9.53]	[5.19]	[3.48]
Spot Crash			0.16		0.37**		-0.37
			[0.32]		[2.22]		[-1.30]
Spot Jump			-0.15		0.46**		0.45
			[-0.31]		[2.69]		[1.56]
Fwd Crash				9.99		10.71	17.89
				[1.51]		[2.17]	[1.47]
Fwd Jump				32.91***		-4.58	-16.63
				[4.49]		[-0.41]	[-0.91]

Table 5: Summary Statistics for the Spillover Measure SO_{it}

This table reports the summary statistics for information spillover measures SO_{it} for 48 currencies. The SO_{it} is calculated by the Post–Least Absolute Shrinkage and Selection Operator (LASSO) to make rolling 1–month ahead currency excess return forecasts using all countries' lagged forward discount as candidate predictors.

	Spillover Measures							
Currencies	Num. Obs	Mean	STD	MIN	25 pct	50 pct	75 pct	MAX
Australian $	257	0.51	0.24	-0.18	0.36	0.50	0.69	1.00
Austrian Schil	257	0.50	0.23	-0.01	0.33	0.48	0.68	1.00
Belgian Franc	257	0.49	0.23	-0.01	0.33	0.48	0.67	0.99
Brazilian Real	257	0.53	0.29	-0.09	0.33	0.52	0.78	1.10
Bulgarian LEV	257	0.49	0.23	-0.04	0.32	0.50	0.67	1.03
Canadian $	257	0.49	0.24	-0.04	0.32	0.49	0.66	0.96
Chinese Yuan	257	0.49	0.26	-0.04	0.31	0.48	0.70	1.08
Czech Koruna	257	0.51	0.27	-0.01	0.29	0.51	0.73	1.01
Danish Krone	257	0.50	0.23	0.00	0.32	0.49	0.70	0.98
Neth. Guilder	257	0.49	0.23	0.00	0.32	0.49	0.66	0.99
Egyptian Pound	257	0.56	0.27	-0.14	0.34	0.56	0.79	1.17
Euro	257	0.49	0.23	-0.04	0.32	0.49	0.69	0.95
Finnish Markka	257	0.49	0.23	-0.01	0.32	0.49	0.67	0.96
French Franc	257	0.49	0.23	-0.01	0.32	0.48	0.68	0.93
German Mark	257	0.49	0.23	-0.01	0.32	0.48	0.68	0.95
Greek Drachma	257	0.50	0.23	-0.01	0.32	0.49	0.68	0.99
HongKong $	257	0.48	0.25	0.00	0.27	0.46	0.66	0.98
Hungarian HUF	257	0.53	0.27	-0.07	0.34	0.54	0.73	1.13
Indian Rupee	257	0.50	0.24	-0.01	0.35	0.49	0.69	1.00
Indonesian Rupiah	257	0.61	0.31	-0.07	0.39	0.62	0.88	1.13
Israeli Shekel	257	0.50	0.25	-0.01	0.32	0.48	0.69	1.00
Italian Lira	257	0.50	0.23	-0.01	0.34	0.48	0.67	0.95
Japanese Yen	257	0.46	0.31	-0.17	0.22	0.43	0.72	1.16
Kenyan Schilling	257	0.49	0.26	-0.04	0.29	0.50	0.71	1.01

Table 5 – Continued

This table reports the summary statistics for information spillover measures SO_{it} for 48 currencies. The SO_{it} is calculated by the Post–Least Absolute Shrinkage and Selection Operator (LASSO) to make rolling 1–month ahead currency excess return forecasts using all countries' lagged forward discount as candidate predictors.

	Spillover Measures							
Currencies	Num. Obs	Mean	STD	MIN	25 pct	50 pct	75 pct	MAX
Kuwaiti Dinar	257	0.49	0.24	0.00	0.31	0.49	0.68	0.99
Mexican Peso	257	0.51	0.27	-0.06	0.31	0.52	0.69	1.16
Malasian Ringgit	257	0.56	0.26	-0.15	0.38	0.56	0.74	1.14
Moroccan Dirham	257	0.51	0.23	-0.04	0.35	0.51	0.69	1.28
Norwegian Krone	257	0.50	0.25	0.00	0.31	0.48	0.69	1.06
New Zealand $	257	0.52	0.26	-0.02	0.33	0.53	0.72	1.08
Philippine Piso	257	0.50	0.24	-0.10	0.33	0.51	0.67	1.15
Polish Zloty	257	0.54	0.27	-0.05	0.35	0.57	0.75	1.07
Pakistani Rupee	257	0.49	0.26	-0.04	0.29	0.48	0.67	1.00
Portuguese Escudo	257	0.49	0.23	-0.02	0.32	0.49	0.68	0.96
South Africa	257	0.53	0.29	-0.10	0.34	0.52	0.77	1.04
Russian Rouble	257	0.50	0.27	-0.13	0.30	0.50	0.70	1.02
South Korean	257	0.51	0.25	-0.06	0.33	0.51	0.67	1.02
Swiss Franc	257	0.50	0.26	-0.03	0.31	0.49	0.70	1.00
Singarpore $	257	0.50	0.20	-0.01	0.34	0.50	0.63	0.95
Swedish Krona	257	0.48	0.25	-0.07	0.29	0.46	0.69	0.99
Saudi Riyal	257	0.48	0.26	-0.05	0.28	0.47	0.68	0.98
New Romanian	257	0.52	0.25	-0.04	0.33	0.54	0.70	1.03
Spanish Peseta	257	0.49	0.23	-0.01	0.32	0.48	0.68	0.97
Slovenian Tolar	257	0.49	0.23	-0.02	0.32	0.49	0.67	0.98
New Turkish	257	0.52	0.27	-0.10	0.35	0.54	0.72	1.00
Taiwarn new $	257	0.48	0.23	0.00	0.30	0.47	0.66	0.96
Thai Baht	257	0.51	0.23	-0.01	0.35	0.49	0.69	1.11
UK Pound	257	0.48	0.25	-0.01	0.31	0.47	0.68	1.02

Table 6: Single Sorts for Spillover Portfolios

This table reports the average monthly excess returns for each SO_{it}–quintile portfolio. Specifically, at the end of each month, we form quintile portfolios based on SO_{it} over our sample periods and these portfolios are held for one month. The one–fifth of lowest SO_{it} are allocated to the first portfolio, and the next fifth is allocated to portfolio 2, and so on, and the one–fifth of all currencies with highest SO_{it} are allocated to the fifth portfolio. Panels A, B, and C are corresponding to the full sample, the sample of developing countries, and that of developed countries. Numbers in the brackets are t–statistics based on Newey–West standard errors.

Panel A: All Countries

		Quintiles				
Statistics	Weak	Q2	Q3	Q4	Strong	SMW
Mean	-0.543	-0.071	0.06	0.144	0.508	1.051
t Stats.	[-2.73]	[-0.50]	[0.42]	[1.29]	[3.57]	[5.65]
SR	-0.171	-0.032	0.026	0.061	0.223	0.363
Q25	-1.66	-1.08	-1.33	-1.04	-0.66	-0.45
Q75	1.03	1.07	1.33	1.26	1.85	2.25
Obs	255	255	255	255	255	255

Panel B: Developing Countries

		Quintiles				
Statistics	Weak	Q2	Q3	Q4	Strong	SMW
Mean	-0.67	-0.09	0.01	0.21	1.11	1.79
t Stats.	[-2.24]	[-0.62]	[0.09]	[1.94]	[5.84]	[5.49]
SR	-0.14	-0.04	0.01	0.12	0.37	0.34
Q25	-1.62	-0.59	-0.54	-0.60	-0.08	-0.55
Q75	1.12	0.80	1.02	1.05	2.65	3.39
Obs	255	255	255	255	255	255

Panel C: Developed Countries

		Quintiles				
Statistics	Weak	Q2	Q3	Q4	Strong	SMW
Mean	-0.43	-0.19	-0.06	0.03	0.11	0.54
t Stats.	[-2.01]	[-1.08]	[-0.36]	[0.17]	[0.72]	[3.05]
SR	-0.12	-0.07	-0.02	-0.01	0.05	0.19
Q25	-1.61	-1.72	-1.68	-1.55	-1.31	-0.85
Q75	1.58	1.58	1.58	1.59	1.52	1.36
Obs	255	255	255	255	255	255

Table 7: Correlations of SMW and Factors

This table shows correlation coefficients between SO_{it} portfolio returns and conventional factors which relate to currency returns. RX and HML_{Lustig} are the level and slope factors of excess returns. MKTRF, SMB, HML, RMW, and CMA are Fama–French five factors downloaded from Kenneth French's data library. Panels A, B, and C are corresponding to the samples of all countries, developing countries, and developed countries.

Panel A: All Countries

	Weak	Q2	Q3	Q4	Strong	SMW
RX	0.08	0.09	0.17	0.18	0.17	0.04
HML_{Lustig}	-0.01	-0.05	0.00	0.08	0.05	0.04
MKTRF	0.08	0.03	0.05	0.10	0.01	-0.08
SMB	-0.04	0.01	0.02	-0.04	0.03	0.07
HML	-0.01	-0.05	0.00	0.08	0.05	0.04
RMW	-0.10	-0.03	-0.01	0.00	-0.05	0.08
CMA	-0.12	-0.10	0.01	-0.09	-0.04	0.10

Panel B: Developing Countries

	Weak	Q2	Q3	Q4	Strong	SMW
RX	0.16	0.11	0.17	0.01	0.22	0.07
HML_{Lustig}	-0.05	0.03	0.01	0.05	0.10	0.17
MKTRF	0.07	0.07	0.15	-0.04	-0.01	-0.02
SMB	-0.12	-0.03	0.04	-0.09	0.08	0.21
HML	-0.09	-0.19	-0.01	0.04	0.09	0.17
RMW	-0.04	-0.08	-0.12	0.06	-0.01	-0.01
CMA	-0.05	-0.10	0.00	0.04	0.10	0.13

Panel C: Developed Countries

	Weak	Q2	Q3	Q4	Strong	SMW
RX	0.10	0.12	0.11	0.15	0.16	0.02
HML_{Lustig}	-0.02	-0.02	-0.03	0.03	0.04	0.06
MKTRF	0.12	0.07	0.02	0.09	0.06	-0.10
SMB	-0.07	0.00	0.02	0.05	0.02	0.10
HML	-0.20	-0.11	-0.05	-0.01	-0.01	0.24
RMW	-0.11	-0.07	-0.03	-0.03	-0.01	0.12
CMA	-0.17	-0.11	-0.06	-0.09	-0.08	0.14

Table 8: Factor–Adjusted Returns

This table reports the factor–adjusted returns for each SO_{it}–quintile portfolios and SMW. The results are based on the time–series regressions of SO_{it} portfolio returns on conventional factors. Alphas are the factor–adjusted returns. RX and HML_{Lustig} are level and slope factors of currency excess returns. MKTRF, SMB, HML, RMW, CMA are the Fama–French five factors. The numbers in the brackets are the t–statistics adjusted by Newey–West standard errors. ***, **, and ** represent significance at 1%, 5%, and 10% level, respectively.

	Weak			Q3			Strong			SMW		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Alpha	-0.65*	-0.60*	-0.55*	0.08	0.10	0.07	0.55***	0.61**	0.62***	1.20***	1.21***	1.17***
	[-1.70]	[-1.80]	[-1.68]	[0.51]	[0.13]	[0.413]	[2.74]	[2.42]	[2.86]	[3.23]	[3.94]	[3.68]
RX	15.97*		18.06*	23.66***		24.53***	20.73**		24.45***	4.76		6.39
	[1.79]		[1.67]	[3.39]		[3.63]	[2.38]		[2.87]	[0.55]		[0.74]
HML_{Lustig}	-4.92		-7.87	-6.15		-6.18	-0.73		2.08	4.19		9.95
	[-0.37]		[-0.56]	[-1.02]		[-0.83]	[-0.09]		[0.23]	[0.27]		[0.62]
MKTRF		3.19	1.78		3.44	0.42		-2.20	-7.24		-5.39	-9.02
		[0.57]	[0.25]		[0.76]	[0.08]		[-0.50]	[-1.52]		[-1.00]	[-1.64]
SMB		-10.91	-12.08		1.55	-0.14		0.26	-1.59		11.17	10.49
		[-1.10]	[-1.27]		[0.33]	[-0.03]		[0.07]	[-0.42]		[1.25]	[1.25]
HML		-12.58	-14.02		-2.26	-4.01		6.47	5.12		19.05**	19.14**
		[-1.41]	[-1.64]		[-0.37]	[-0.64]		[1.11]	[0.88]		[2.23]	[2.35]
RMW		-8.26	-8.91		2.42	1.28		-6.03	-7.63		2.23	1.27
		[-0.89]	[-0.99]		[0.41]	[0.25]		[-0.84]	[-1.06]		[0.21]	[0.12]
CMA		-0.81	0.22		4.77	5.68		-9.03	-9.04		-8.22	-9.26
		[-0.07]	[0.02]		[0.49]	[0.59]		[-0.81]	[-0.83]		[-0.58]	[-0.65]

Table 9: Double Portfolio Sorts

This table reports monthly excess returns for double–sorted portfolios. All currencies in the sample are first sorted on either lagged forward discounts or lagged excess returns into quartile portfolios. Next, currencies within each of the quartile portfolios are allocated into four SO_{it} portfolios depending on SO_{it}. We report monthly excess returns in percent for each portfolio and all strong–minus–weak portfolios. Numbers in brackets are Newey–West HAC t–statistics. ***, **, and ** represent significance at 1%, 5%, and 10% level, respectively.

Panel A: MOM and Spillover–All Countries					Panel B: CT and Spillover–All Countries				
Spillover	MOM Quartile				Spillover	CT Quartile			
Quartile	L	Q2	Q3	H	Quartile	L	Q2	Q3	H
W	-1.58	-0.16	0.19	0.12	W	-1.56	-0.24	0.05	-0.18
Q2	-0.18	-0.07	0.01	0.20	Q2	-0.21	-0.05	0.13	0.31
Q3	-0.15	-0.03	0.13	0.41	Q3	-0.17	0.02	0.11	0.52
S	-0.18	0.00	0.03	1.10	S	-0.22	0.02	0.02	1.18
SMW	1.40	0.16	-0.16	0.98	SMW	1.34	0.26	-0.03	1.36
t Stats.	[3.28]	[1.08]	[-1.45]	[4.83]	t Stats.	[3.69]	[2.37]	[-0.22]	[4.08]
Panel C: MOM and Spillover–Developing Countries					Panel D: CT and Spillover–Developing Countries				
Spillover	MOM Quartile				Spillover	CT Quartile			
Quartile	L	Q2	Q3	H	Quartile	L	Q2	Q3	H
W	-0.04	0.17	0.33	0.40	W	-0.31	-0.02	0.01	0.39
Q2	-1.47	-0.22	0.32	-0.07	Q2	-1.09	-0.17	-0.38	0.56
Q3	-0.07	-0.10	0.18	1.12	Q3	-0.03	0.04	0.12	1.02
S	-0.14	-0.02	0.18	2.36	S	-0.05	0.14	-0.01	2.20
SMW	-0.11	-0.19	-0.15	1.96	SMW	0.26	0.16	-0.01	1.82
t Stats.	[-0.39]	[-0.47]	[-0.50]	[5.29]	t Stats.	[2.14]	[1.78]	[-0.56]	[4.17]
Panel E: MOM and Spillover–Developed Countries					Panel F: CT and Spillover–Developed Countries				
Spillover	MOM Quartile				Spillover	CT Quartile			
Quartile	L	Q2	Q3	H	Quartile	L	Q2	Q3	H
W	-1.67	-0.12	-0.25	0.15	W	-1.85	-0.07	0.02	0.15
Q2	-0.07	-0.12	-0.07	-0.07	Q2	-0.18	-0.07	0.02	-0.04
Q3	-0.14	-0.06	0.04	0.16	Q3	-0.20	-0.09	-0.11	0.19
S	-0.09	-0.10	0.02	0.23	S	-0.10	-0.11	-0.13	0.36
SMW	1.58	0.02	0.28	0.08	SMW	1.75	-0.04	-0.15	0.22
t Stats.	[3.58]	[0.18]	[2.01]	[0.43]	t Stats.	[2.89]	[-0.37]	[-0.72]	[1.99]

Table 10: Fama and MacBeth Regressions

This table shows average coefficients of Fama–MacBeth regressions of individual currencies' excess returns on SO_{it}, lagged excess return, lagged forward discount. Numbers in brackets are t–statistics. ***, **, and ** represent significance at 1%, 5%, and 10% level, respectively. Panels A, B, and C are corresponding to the samples of all countries, developing countries, and developed countries.

Panel A: All Countries							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SO_{it}	0.012***			0.011***	0.008**		0.006**
	[3.91]			[2.98]	[2.42]		[2.03]
Excess Return		0.274***		0.188***		0.092***	0.106*
		[3.57]		[2.82]		[3.04]	[1.77]
Fwd Disct			0.439***		0.441***	0.462***	0.502***
			[4.62]		[4.72]	[5.51]	[6.04]
Panel B: Developed Countries							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SO_{it}	0.007***			0.082**	0.043		0.005*
	[2.85]			[2.33]	[1.38]		[1.82]
Excess Return		0.10***		-0.102		0.066**	-0.001
		[3.42]		[-1.00]		[2.15]	[-1.00]
Fwd Disct			0.31**		0.35**	0.298**	0.389**
			[2.13]		[2.46]	[1.98]	[2.59]
Panel C: Developing Countries							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SO_{it}	0.017***			0.022***	0.007*		0.011***
	[3.87]			[2.82]	[1.97]		[3.12]
Excess Return		0.234**		0.001		0.016	-0.15
		[2.54]		[0.12]		[0.33]	[-0.86]
Fwd Disct			0.50***		0.468***	0.559***	0.544***
			[3.86]		[3.52]	[3.80]	[3.55]

Table 11: Macroeconomic Risk

This table reports the regression results of SMW returns in month $t+1$ on common macroeconomic factors in month t. The macroeconomic factors are downloaded from Ludvigson's website.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
F1	0.002										0.023***
	[0.39]										[2.89]
F2		-0.014*								-0.006	-0.005
		[-1.87]								[-0.59]	[-0.45]
F3			-0.012*							-0.011	-0.009
			[-2.18]							[-1.63]	[-1.21]
F4				0.043***						0.027**	0.035***
				[4.79]						[2.34]	[2.83]
F5					0.036***					0.017*	0.016
					[4.37]					[1.74]	[1.57]
F6						0.026**				0.016	0.014
						[2.31]				[1.41]	[1.16]
F7							0.011				0.001
							[0.84]				[0.06]
F8								-0.011			0.003
								[-0.82]			[0.21]
F1_3									-0.004		-0.011**
									[-1.21]		[-2.43]
R Square	0.001	0.014	0.019	0.083	0.07	0.021	0.003	0.003	0.006	0.122	0.152

Figure 1: Cumulative Returns for Long–Short SO_{it} Portfolios

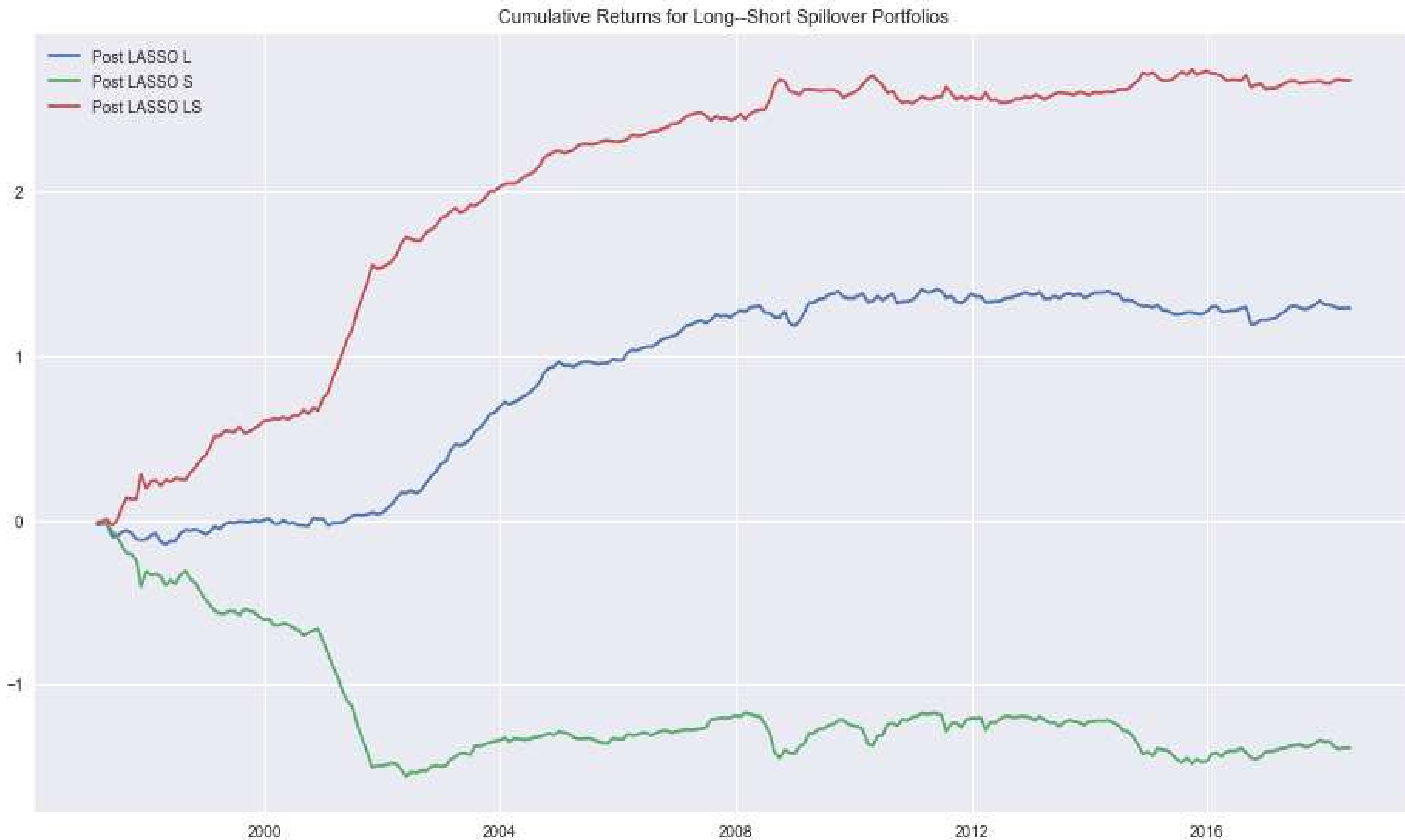

Figure 2: Monthly Returns for Long–Short SO_{it} Portfolios

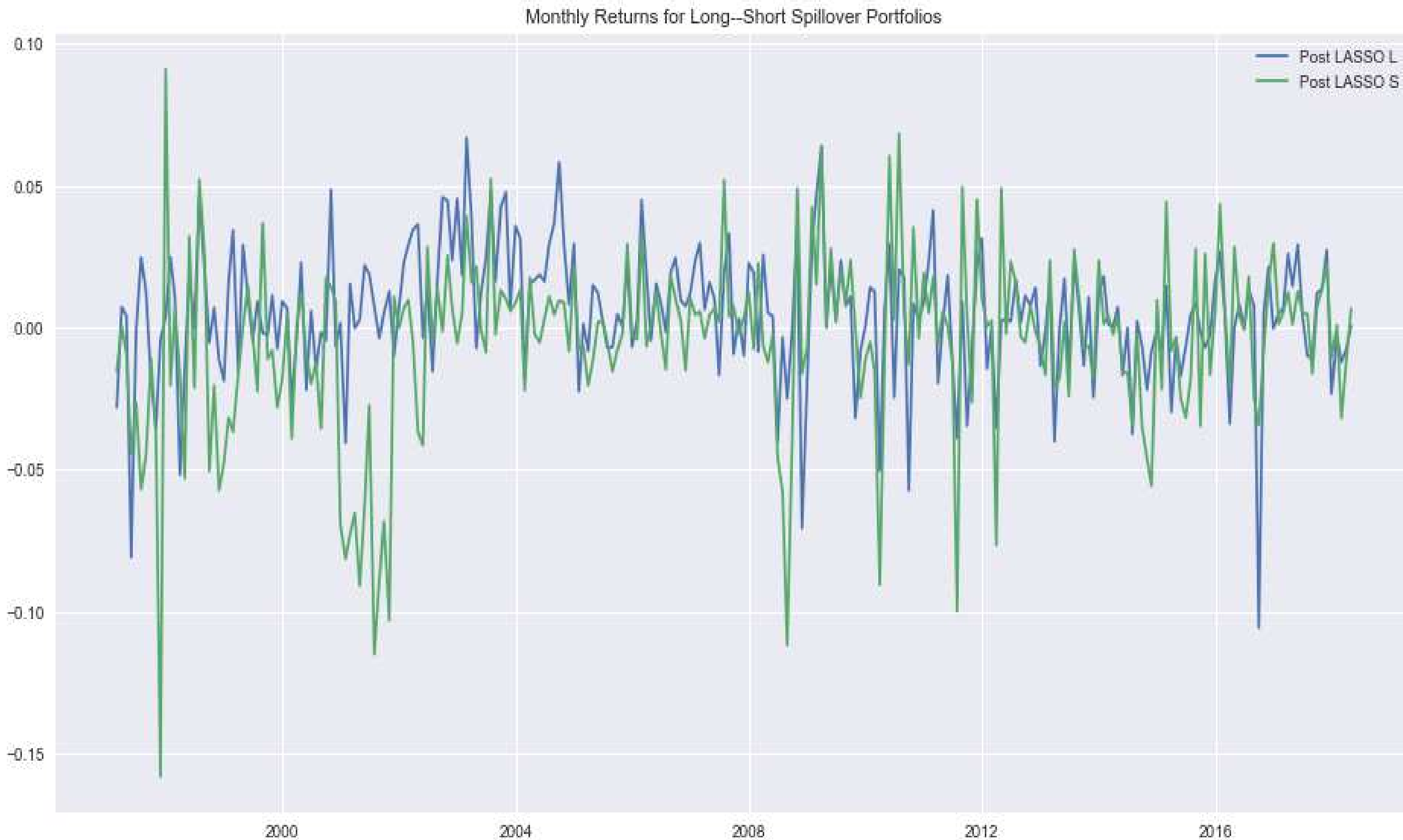

Figure 3: Graphs for Portfolio Sorts