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Three essays on empirical asset pricing

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Abstract

This thesis consists of three chapters. In Chapter 1, I show that returns to currency carry and momentum strategies are compensations for the risk of US monetary policy uncertainty (MPU), with risk exposures explaining 96% of their cross-sectional return variations. The findings are consistent with an intermediary-based exchange rate model. Higher *MPU* triggers position unwinding by the intermediary, which decreases the returns of currency with high interest rate or appreciation, while that with low interest rate or depreciation earns positive returns. Different responses stem from the long and short behavior of the intermediary. The explanatory power of US *MPU* risk is robust and unrelated to commonly used risk factors.

In Chapter 2, I document a novel source of time variations in the cross-sectional inflation risk premium. A consumption-based asset pricing model with inflation non-neutrality and ambiguity shows that the investor's fear of inflation model misspecification ties up the inflation beta and ambiguity beta of individual stocks. As a result, the inflation ambiguity premium amplifies or counteracts the cross-sectional inflation risk premium, whose net effect largely depends on the co-movement of inflation and inflation ambiguity, named as *nominal-ambiguity correlation* (NAC). Empirically, positive *NAC* at the current quarter predicts in the following quarter a loss of *quarterly* return of -4.88% (-2.87%) for a zero-investment high-minus-low value-weighted (equal-weighted) portfolio, obtained by sorting on all individual stocks based on their exposures to inflation risk. The time-varying *NAC* also explains well the dynamics of inflation premium at the industry-level. The ambiguity channel differs from the existing resolutions both theoretically and empirically.

In Chapter 3, I propose a two-country affine model of exchange rates to obtain

a Forex factor. I show that this factor is an important driver of the stock market risk premium. Not only it contributes to a sizable portion of exchange rate volatility, but also outperforms the commonly used financial and macroeconomic variables in terms of predicting stock excess returns. The predictive power is robust with respect to forecasting horizons, and to different industry and characteristic portfolios. In addition, the cross-sectional study shows that the Forex-specific factor has substantial explanatory power for cross-section return differences of industry portfolios, the performance is better than the Fama-French three factor model and is comparable with that of the up-to-date five factor model.

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Table of Contents

List of Figures

List of Tables

Chapter 1 Introduction

In the domain of asset pricing and financial economics, there exist lots of puzzles or anomalies. While the most famous "equity premium puzzle" has received extensive discussions, other anomalies in equity and currency market also pose significant challenges to standard asset pricing theory. Nevertheless, the related academic literature is comparably small, and researchers have little consensus on what caused these anomalies.

In this dissertation, I handle three puzzling facts related to the stock and currency markets, which have not received satisfactory explanations from the literature. In the first chapter, I seek to understand the high returns to the two most well-known currency strategies: the carry and momentum. As comprehensively surveyed by Burnside et al. (2011), they deliver high profits and Sharpe ratios that are comparable to the US aggregate stock market, which is the central quantity that the literature of "equity premium puzzle" tries to address. However, up to now, there are few resolutions explaining the currency carry and momentum strategies in a unified way. In fact, this is a more serious challenge to the financial economist since compared with the US stock market, the trading volume of FX market is several times larger, and the market frictions are smaller. The trading cost is low, and there are no explicit short-selling constraints.

Therefore, I propose a unified, risk-based explanation for the currency carry and momentum. The key risk factor is the US monetary policy uncertainty (MPU). I show that risk exposures of different carry or momentum currencies explain almost perfectly their cross-sectional return variations, with the cross-sectional R^2 of 96%. The novel evidence hence directly points to the common risk source underlying these two popular currency strategies. Furthermore, the main conclusions are robust to various settings or controls. While Burnside et al. (2011) already suggest that the standard finance theory does a poor job of reconciling these returns, I use the intermediary based asset pricing theory recently proposed by, e.g., He and Krishnamurthy (2013) to understand my findings. I show that my model can generate the profitability of currency carry and momentum strategies. Moreover, the model also implies decreasing exposures to the risk of US *MPU* at the cross-section of carry or momentum. These two predictions match the key features I find from the data.

In the second chapter, I switch my focus to the US stock market. I address another well-known puzzling fact: why inflation risk is not priced in the stock market. Albeit the significant role in the bond market, dating back to Fisher (1930), the long-standing discussions in the stock markets have not concluded. The classical study such as Fama and Schwert (1977) find that the relation between inflation and aggregate stock returns is weak and sometimes contradicts the theory. Subsequent papers do not provide encouraging evidence on this issue either, though with quite different measures of inflation risk or econometric testing procedures.

My angle of tackling this problem follows the recent attempt of looking at the individual stocks. Considerable firm heterogeneity makes some of them more exposed to the inflation shock. The large cross-sectional spreads of exposures make it an attractive laboratory to study the relation between inflation risk and stock returns. I show that the measured inflation risk premium from the cross-section of stocks is subject to strong time-variations. The time-varying component is new and tied to investor's concern of inflation model misspecification.

Specifically, in a framework that goes beyond the rational expectation paradigm, the investor also displays concern over the model uncertainty underlying the economy, or *Knightian* uncertainty. As a result, the equilibrium time-varying risk premium reflects the pricing of time-varying Knightian uncertainty. This is especially true at the cross-section of stocks, since stock's exposures to the inflation shock and ambiguity shock are tightly linked. I find that the co-movement between inflation and ambiguity, named as *nominal-ambiguity correlation*, significantly drives the time-varying cross-sectional inflation premium. Positive *NAC* at the current quarter predicts in the following quarter a loss of *quarterly* return of -4.88% (-2.87%) for a zero-investment high-minus-low value-weighted (equal-weighted) portfolio, obtained by sorting on all individual stocks based on their exposures to inflation risk. Such an effect is economically large and statistically significant, and is robust under a variety of settings. Similar evidence also presents at the industry-level. Moreover, I propose a new and simple market-timing strategy for speculating on the inflation risk cross-sectionally. The strategy buys the portfolio with the lowest inflation beta and short-sells that with the highest inflation beta, when the current *NAC* is positive, and vice versa. The performance of the strategy directly sheds light on the economic benefit of the ambiguity channel. I find that this simple conditional strategy based on the sign of *NAC* yields an annualized average excess return of 9.58% and 5.77%, with the annualized Sharpe ratio of 0.59 and 0.51 for value- and equal-weighted portfolios respectively. Both returns are highly significant and cannot be explained by the CAPM, Fama-French three- or five-factor models.

In Chapter 3, I ask another interesting question. Are the stock and currency markets segmented? In spite of the fact that the literature tries to understand various anomalies in these two markets, there are comparably much fewer discussions on whether there exist common risk factors *between* them. I thereby implement the formal empirical test by relying on the insights from the simplest finance theory. Since the pricing kernel of the representative investor should be key to understand both markets, I propose an affine term structure model to directly estimate the pricing kernels from a large panel of macroeconomic and financial data. The model input covers the inflation, economic growth, bond yields, currency returns, and currency option implied volatility. Due to the model nonlinearity, I employ the particle filter method to run likelihood-based inference.

In contrast to the previous findings in the literature, I find that there is considerable risk-sharing among currency and stock markets. From the estimated pricing kernel, I show that the factor that accounts for a large portion of currency volatility also strongly predicts the US stock market excess returns (named as Forex-specific factor). The predictive power outperforms the commonly used financial and macroeconomic variables, and is robust with respect to different forecasting horizons, industry and characteristic portfolios. In addition, the cross-sectional study shows that the Forex-specific factor has substantial explanatory power for cross-section return differences of industry portfolios. The evidence thus is encouraging on connecting two important financial markets.

Overall, this thesis provides new insights into helping people understand some important puzzles in the financial markets. The currency market anomalies are tightly linked to the US monetary policy uncertainty. The commonly documented weak relation between inflation risk and stock returns is due to the strong time-variations induced by the inflation ambiguity. And finally, I show that there is a share of risk among currency and US stock markets, by working with an estimated SDF model using information from a large panel of macroeconomic and financial data.

Chapter 2 Currency Carry, Momentum, and US Monetary Policy Uncertainty

2.1 Introduction

The foreign exchange (FX) market is the largest financial market in the world. The triennial survey from the Bank for International Settlements (BIS) reports that the daily FX trading volume is estimated to be \$5.1 trillion as of 2016. Additionally, the currency investment is very profitable. Among the most popular currency trading strategies, the cross-section of carry and momentum trade yield average monthly excess returns of 0.58% and 0.51% respectively, during the period from January 1985 to August 2017.[1] Since the FX market is very liquid with low trading costs and easy access to the short-selling, a reasonable explanation for the profitability is that their returns reflect risk compensations. However, little is known about what are the common risk sources underlying these two types of trade, especially given their weak correlation. Existing resolutions based on the standard finance theory receive dismal performance empirically (see a review by Burnside et al., 2011).

The contribution of this paper is to provide a unified risk-based explanation for the profitability of FX carry and momentum strategies. By using the US Monetary Policy Uncertainty (MPU) index of Baker et al. (2016), I find that the exposures to the US MPU shocks can explain the cross-sectional return dispersions of currency carry and momentum trade, with the R^2 reaching 98% for both cross-sections. The explanatory power remains almost unchanged at 96% when studying their joint

[1]These returns are from the viewpoint of a US investor and net of transaction costs. The cross-section of carry (momentum) trade buys the basket of currencies with the highest and shorts that with the lowest interest rate differentials (realized appreciations) against USD.

cross-section of returns. More specifically, I find that the top carry and momentum portfolios have lower and negative exposures (betas) to the risk of US *MPU*, whereas their peers at the bottom have higher and positive betas. The beta spreads are statistically significant, which translates to a negative and significant price for the US *MPU* risk, with the Shanken t-statistic of -2.54. The results are similar if instead using the realized variance of 10-year US Treasury yields as the proxy for the US *MPU*, with the cross-sectional R^2 of 90% and the Shanken t-statistic of -2.49.

To reconcile the novel findings, I study an exchange rate model following the spirit of Gabaix and Maggiori (2015) and Mueller et al. (2017). The model highlights the role of sophisticated financial intermediary as the marginal investor in the FX market. In the model, the financial intermediary (called the *financier*) accommodates the cross-border asset flows between the US and foreign countries. She holds either the foreign currencies or USD arising from the bilateral imbalanced flows. Though the financier aims to profit from bearing such imbalance, the presence of financial constraints restricts the risk-taking and gives rise to different incentives of holding different currencies. Specifically, the intermediary is more willing to hold the foreign currency with high interest rate because of the attractive bond yield. And since realized currency returns negatively predict future foreign demand for US assets, the foreign currency with realized appreciation against USD has lower expected supply. Hence the financier will hold it today so as to benefit from the potential appreciation. By the same logic, the financier tends to short the foreign currency with low interest rate or realized depreciation against USD. When the US *MPU* becomes higher, the financial constraint of the intermediary tightens, which triggers unwinding in both long and short positions. As a result, currency with high interest rate or appreciation experiences negative returns, whereas that with low interest rate or depreciation provides a hedge, in line with the explanatory power of US *MPU* risk for FX carry and momentum returns.

I provide further evidence to show that rising US *MPU* indeed tightens the intermediary constraints. By using the gross equity flows between foreign countries and the US as the measure for financial frictions of the intermediary sector, I find that the US *MPU* shocks significantly and negatively predict the changes in these flows. The predictive power is robust after controlling for other effects such as the demand shocks from international equity investors. Alternatively, by augmenting the FX carry and momentum portfolios with the well-known cross-sectional portfolios from other asset classes, I find that the negative prices of *MPU* risk are also manifested in stocks, bonds, and options. The consistent risk prices echo the argument following He et al. (2017) that the variables driving financial frictions of the intermediary sector are likely to help price many asset classes. I show that the cross-sectional R^2 for these augmented testing assets ranges from 59% to 82%.

To corroborate the main findings, I carry out a battery of robustness checks. First, the results are invariant to using different testing procedures such as the Fama-MacBeth regression or the GMM estimation. The results are even stronger if using the factor-mimicking portfolio return as the risk factor in the test. Second, after controlling for other risk factors and measures of financial frictions, I find that the unified pricing power of *MPU* risk on FX carry and momentum returns is not affected. Third, the currency-level study alike points to negative and significant price of *MPU* risk. In particular, the high interest rate currency such as the Australian Dollar (AUD) indeed has low and negative *MPU* beta, in contrast to the low interest rate currency such as the Japanese Yen (JPY). Last but not least, the asset pricing results are robust under time-varying *MPU* betas, different subsamples; formation of momentum portfolios; base currencies of the trade; and limits to arbitrage such as the idiosyncratic volatility and skewness.

Related literature The paper contributes to a large strand of literature towards understanding the risk sources of high returns to currency strategies. Most of the previous papers focus on the cross-section of carry trade. Lustig and Verdelhan (2007) interpret its returns as exposures to the US consumption growth risk, and Lustig et al. (2011) further reconcile its profitability via the slope factor constructed from the carry trade portfolios. Based on the ICAPM argument, Menkhoff et al. (2012a) find that changes in global FX volatility help explain the carry returns. Among other resolutions, Burnside et al. (2010) argue that the carry trade returns reflect a peso problem, and Lettau et al. (2014) show that the US downside risk is an important risk factor for currency and other asset classes. The more recent focus is on understanding the currency momentum. Burnside et al. (2011) and Menkhoff et al. (2012b) find that the correlation between carry and momentum returns is small, and traditional risk factors cannot explain the cross-section of momentum returns. Filippou et al. (2017) show that the global political risk can reconcile the momentum returns. Bae and Elkamhi (2017) further price the joint cross-section of carry and momentum by the risk of global equity correlation. My paper is tightly linked with all these articles. I show empirically that the risk of US monetary policy uncertainty can explain the returns to currency carry and momentum strategies jointly. The unified risk-based resolution is robust and unrelated to existing risk factors. The explanatory power is fully consistent with an intermediary-based asset pricing model and stems from its unique impact on the financial constraints of the intermediary sector. In particular, the theoretical mechanism extends discussions in Brunnermeier et al. (2008), who show that the crash risk due to the position unwinding of carry trades may help explain the violation of the UIP.

This article is also related to the recent literature on studying the asset pricing implications of policy uncertainty. Besides the theoretical framework of Pástor and Veronesi (2012) and Pástor and Veronesi (2013), Brogaard and Detzel (2015) empirically evaluate the pricing of policy uncertainty in the stock market via the Economic Policy Uncertainty index of Baker et al. (2016). Nevertheless, the discussion within the FX market is still at the infant stage, with some exceptions including, e.g., Berg and Mark (2017). In particular, my paper is closely related to Mueller et al. (2017), who find that the profitability of the carry trade and the strategy that buys foreign currencies and short-sells the USD is significantly higher during the FOMC announcements. While they study the high-frequency behavior of these currency returns and interpret the results as compensations for the risk of US MPU, my paper differs from theirs in two important perspectives. First, my paper follows the standard asset pricing test by examining and reconciling the well-known currency risk premium anomalies at the monthly frequency. Moreover, they do not study the currency momentum and further the unified risk-based explanation for the FX carry and momentum returns. I thus treat the conclusions from my paper as important complements to theirs in the sense that we both highlight the value of US MPU in understanding the currency risk premium, at both high- and low-frequency.

2.2 Data and Methodology

2.2.1 Policy uncertainty and shocks to US MPU

As the baseline measure for the US monetary policy uncertainty, I rely on the Monetary Policy Uncertainty (MPU) index built by Baker, Bloom and Davis (2016) (hereafter *BBD MPU* index). The index is constructed as the scaled frequency counts of articles that discuss US monetary policy uncertainty, from hundreds of US daily newspapers covered by Access World News. The first reason for using this news-based measure is the advantage of being model-free and quantifying the subjective uncertainty over US monetary policy. Second, compared with the option-based measures as used in, e.g., Mueller et al. (2017), the MPU index reflects the perception of economy-wide households instead of those only involved in the option market. Moreover, the option-based measure has a component driven by the time-varying risk aversion in addition to the uncertainty (e.g., Bekaert et al., 2013). The contaminating effect from the risk aversion would be large when measuring the uncertainty.[2]

The data of BBD MPU index are available at the monthly frequency from January 1985 to August 2017. To obtain their shocks as the risk factor, I first compute

[2]As alternative monthly measures for the US MPU, I use the realized variance of 1-year and 10-year US Treasury yields computed from the daily data. The details are in Section 2.3.2.

the simple change in MPU level:

$$\Delta MPU_t = MPU_t - MPU_{t-1}. \tag{2.2.1}$$

However, ΔMPU_t is highly correlated with changes in other category-specific BBD policy uncertainty indexes,[3] which confound the identification of shocks to the US MPU. I thus follow the spirit of Petkova (2006) and Della Corte and Krecetovs (2017) by running the orthogonalization:

$$\Delta MPU_t = \alpha + \sum_j \beta_j \Delta EPU_{j,t} + u_t^{MPU}, \tag{2.2.2}$$

where $EPU_{j,t}$ denotes the BBD policy uncertainty index of category-j, and u_t^{MPU} denotes the orthogonal MPU shocks later used in the asset pricing test. For variables on the right-hand side of Equation (2.2.2), I consider four categories that cover Taxes; Fiscal and government spending; Sovereign debt; and National security. The selection follows their relevance for FX markets (see, e.g., Kumhof and Van Nieuwerburgh, 2007; Della Corte et al., 2016), and I show in the Internet Appendix (Table A.6) that subsequent results are not sensitive to other choices.

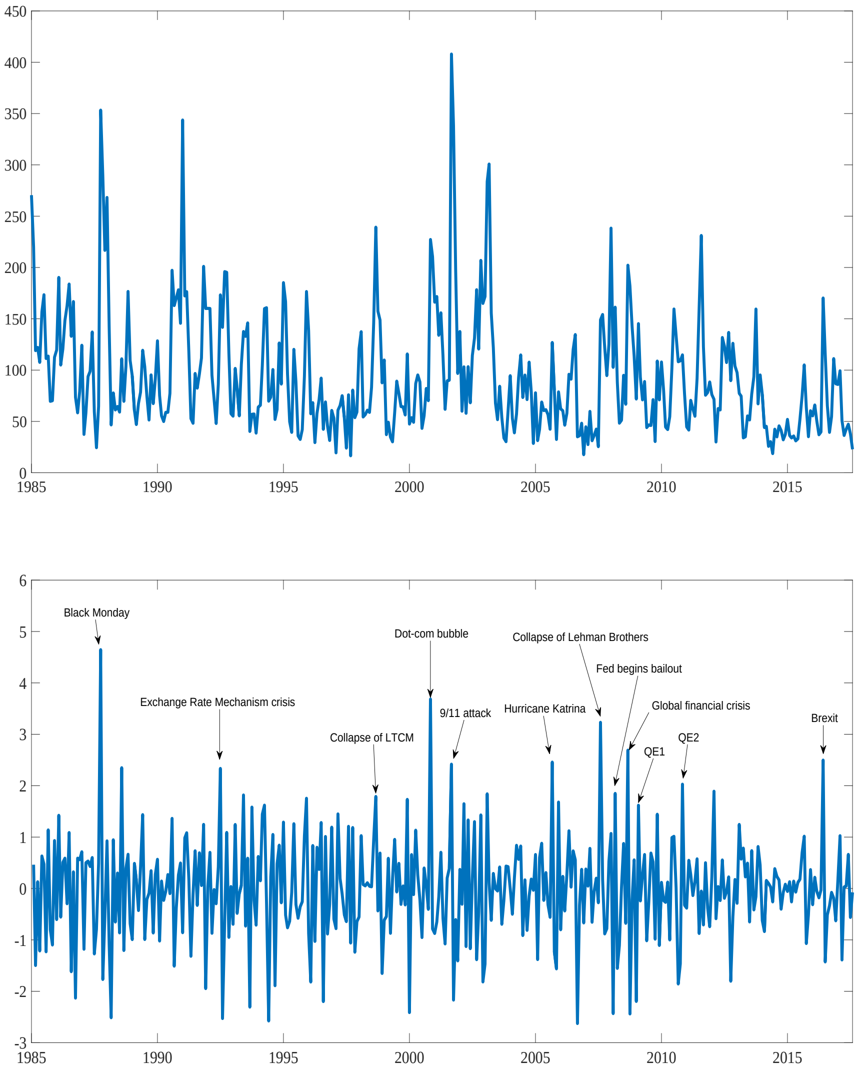
Figure 2.1 plots the original BBD monetary policy uncertainty index (upper panel), as well as the standardized u_t^{MPU} estimated from Equation (2.2.2) (lower panel). The orthogonal shocks u_t^{MPU} capture important periods that are accompanied with sharp changes in the US monetary policy uncertainty, such as the Black Monday, collapse of Long-Term Capital Management (LTCM), bursting of dot-com bubble, 2008 global financial crisis, QE 1 & 2, and Brexit, etc. Table 2.1 then reports the correlation coefficients of u_t^{MPU} with the returns to currency carry and momentum strategies, as well as the innovations in other uncertainty measures. They include the BBD category-specific policy uncertainties used on the right-hand side of Equation (2.2.2), the BBD Economic Policy Uncertainty index, the realized variance of

[3] In addition to the uncertainty over monetary policy, Baker et al. (2016) also builds the policy uncertainty indexes for the categories such as the fiscal policy, sovereign debt, etc.

1-year (IRV 1Y) and 10-year (IRV 10Y) US Treasury yields, the global FX volatility of Menkhoff et al. (2012a), VIX, and the factor-based measures covering the financial, macroeconomic and real sides of US economy from Jurado et al. (2015). For comparison, I also list the correlation coefficients related to ΔMPU_t.

Figure 2.1. US MPU index and its innovations

The upper panel plots the original US monetary policy uncertainty (MPU) index of Baker et al. (2016). The lower panel plots the standardized shocks u_t^{MPU} obtained from Equation (2.2.2). The sample period is from January 1985 to August 2017.



Indeed, from the table, one can find that ΔMPU_t are highly correlated with changes in other uncertainties, even though they are meant to capture different aspects of the economy. ΔMPU_t is also significantly correlated with the carry trade returns, but it does not co-move with the currency momentum returns. After running the orthogonalization, the co-movements of u_t^{MPU} with other uncertainty shocks are much weaker. For example, the correlation coefficient between changes in MPU and EPU reduces from 0.80 to 0.28, and u_t^{MPU} even does not show a significant correlation with the global FX volatility. Importantly, its co-movements with two measures of interest rate uncertainty are not affected, implying that the useful information related to the US MPU is preserved. Furthermore, while other uncertainty shocks are not so related to currency momentum returns, the orthogonal shocks to US MPU (and also the shocks to IRV) are significantly and negatively correlated with both carry and momentum returns.

Table 2.1. Correlation analysis

The table reports the correlation coefficients of returns to currency carry, momentum, and uncertainty shocks. ΔMPU_t denotes the simple change in MPU index of Baker et al. (2016), u_t^{MPU} is the orthogonalized MPU shock obtained from Equation (2.2.2). The uncertainty measures include the BBD policy uncertainty indexes associated with the categories of Taxes, Fiscal & spending, National security, and Sovereign debt; the BBD Economic Policy uncertainty index; the monthly realized variance of 1-year and 10-year Treasury yields; the FX volatility of Menkhoff et al. (2012a); the factor-based measure of US Financial, Macro and Real uncertainty of Jurado et al. (2015). *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels. The sample period is from January 1985 to August 2017.

	ΔMPU_t	u_t^{MPU}	Carry	Mom
ΔMPU_t	1.00			
u_t^{MPU}	0.71***	1.00		
Carry	-0.19***	-0.12**	1.00	
Mom	-0.04	-0.13***	0.03	1.00
Taxes	0.52***	0.00	-0.14***	0.04
Fiscal & spending	0.49***	0.00	-0.11**	0.02
National security	0.57***	0.00	-0.06	0.04
Sovereign debt	0.28***	0.00	-0.13***	0.11**
EPU	0.80***	0.28***	-0.16	-0.01
IRV 1Y	0.30***	0.30***	-0.19***	-0.11**
IRV 10Y	0.23***	0.23***	-0.15***	-0.12**
FX Volatility	0.20***	0.06	-0.31***	0.05
VIX	0.32***	0.16***	-0.27***	0.01
US Financial	0.28***	0.11**	-0.23***	-0.02
US Macro	0.19***	0.01	-0.11**	0.06
US Real	0.11**	0.01	-0.12**	0.01

2.2.2 Currency carry and momentum portfolios

The data for the spot exchange rates and one-month forward rates cover 48 countries and range from January 1985 to August 2017. The data are from the Datastream (Barclays Bank International and Reuters). I remove the Eurozone currencies after the adoption of Euro, and also remove the periods for some currencies when there are violations in the Covered Interest Rate Parities (CIP). To form the carry and momentum portfolios, I use the information from mid-level spot and forward rates, but the portfolio returns are computed by taking into account the bid-ask spreads, following e.g., Menkhoff et al. (2012b).[4]

Denote the mid-spot rate as S_t which represents units of foreign currency per unit of US dollar, and denote the one-month mid-forward rate as F_t. As the proxy for the interest rate differential between the foreign country and the US, I follow the literature by using the forward discount (see e.g., Lustig et al., 2011):

$$i_t^* - i_t \approx f_t - s_t, \tag{2.2.3}$$

where the small letters stand for log terms. Then the one-period log currency excess return rx_{t+1} can be computed as:

$$rx_{t+1} = i_t^* - i_t - \Delta s_{t+1} \approx f_t - s_{t+1}. \tag{2.2.4}$$

To form the carry trade portfolios, I first sort on all currencies' forward discounts at the end of each month. Then each currency is attributed to one of the quintile portfolios, where portfolio 1 (5) consists of currencies with the lowest (highest) interest rate differentials vis-à-vis the United States. To construct the momentum trade portfolios, I sort on currencies' past realized excess returns at the end of each month, where the realized quantities are computed over the past 3-month horizons.[5] Then

[4]These data are also available from Reuters, and Internet Appendix contains more details of how to account for transaction costs when computing portfolio returns. Note that the bid-ask spread data from Reuters are around twice the size of inter-dealer spreads, as documented by Lyons (2001).

[5]Later I provide the robustness checks for other horizons.

five portfolios are formed, where the portfolio 1 (5) contains currencies with lowest (highest) realized excess returns. They are also called the *loser* and the *winner* portfolio respectively. All portfolios are rebalanced monthly, and their excess returns are computed via the equal-weighted scheme.

The first column of each panel in Table 2.2 reports the average monthly excess returns of carry and momentum portfolios, after taking into account the bid-ask spreads. In line with the findings in the literature, the strategy profitability is large and significant. The average monthly high-minus-low return spreads for the carry and momentum portfolios are 0.58% and 0.51%. Furthermore, the returns increase monotonically from the bottom to the top portfolios, revealing the substantial predictive power of interest rate differentials and realized currency returns on future returns. The monotonic order is also supported statistically by the test of monotonic relations (MR) following Patton and Timmermann (2010). I report the p-values of testing the null hypothesis that the portfolio returns are monotonically increasing, which are based on either five portfolios (brackets) or all pair-wise comparisons (parentheses). The null hypothesis cannot be rejected at any conventional confidence levels.

Table 2.2. Statistics of currency carry and momentum portfolios

The table reports the statistics for the currency carry and momentum portfolios. Carry portfolios are obtained by sorting on the forward discounts, and momentum portfolios are obtained by sorting on the realized excess returns over the previous 3-month period. All portfolios are rebalanced monthly, and the reported average monthly excess returns (in percentage) are net of transaction costs. Exposures to the risk of US *MPU* are computed from Equation (2.3.1). The R^2 of these regressions are listed in the last column of each panel. Standard errors are in parentheses and based on Newey and West (1987) with optimal lag selection following Andrews (1991). The excess returns, *MPU* betas and monthly Sharpe ratios (SR) of high-minus-low portfolios are also reported. The monotonicity of portfolio excess returns and *MPU* betas are tested via the monotonic relation (MR) test of Patton and Timmermann (2010), where the p-values are reported based on either five portfolios (brackets) or all pair-wise comparisons (parentheses). The null hypotheses for the tests are the monotonically increasing returns and decreasing betas respectively. The sample period is from January 1985 to August 2017.

	Panel A: Carry				Panel B: Momentum			
	r^e	β_{DOL}	β_{MPU}	R^2	r^e	β_{DOL}	β_{MPU}	R^2
L	-0.22	0.87	0.18	0.68	-0.10	1.02	0.21	0.61
	(0.12)	(0.04)	(0.07)		(0.15)	(0.08)	(0.10)	
2	0.05	0.91	0.05	0.79	-0.02	0.99	0.10	0.79
	(0.11)	(0.03)	(0.05)		(0.12)	(0.05)	(0.06)	
3	0.22	1.01	-0.04	0.86	0.17	1.02	-0.04	0.81
	(0.12)	(0.03)	(0.04)		(0.12)	(0.04)	(0.07)	
4	0.21	1.06	-0.04	0.83	0.23	0.98	-0.07	0.79
	(0.13)	(0.03)	(0.06)		(0.12)	(0.04)	(0.05)	
H	0.36	1.15	-0.16	0.66	0.41	1.00	-0.19	0.62
	(0.17)	(0.06)	(0.09)		(0.14)	(0.07)	(0.10)	
HML	0.58		-0.34		0.51		-0.40	
	(0.16)		(0.15)		(0.15)		(0.17)	
SR	0.21				0.17			
MR	[0.93]		[1.00]		[1.00]		[1.00]	
	(0.93)		(0.98)		(1.00)		(0.92)	

2.3 Empirical Results

2.3.1 Cross-sectional asset pricing test

In this subsection, I test the pricing power of shocks to the US monetary policy uncertainty for the cross-section of carry and momentum portfolios. As the benchmark testing procedure, I use the usual two-stage Fama-MacBeth regression. At the first stage, the return sensitivity to the MPU shocks for each portfolio i is estimated from the time-series regression:

$$rx_t^i = \alpha^i + \beta_{DOL}^i DOL_t + \beta_{MPU}^i u_t^{MPU} + \varepsilon_t^i, \tag{2.3.1}$$

where DOL_t is the dollar factor constructed as the cross-sectional average of excess returns of five carry trade portfolios following Lustig et al. (2011). It can be treated analogously as the market factor in the FX market. Then at the second stage, I run the following cross-sectional regression:

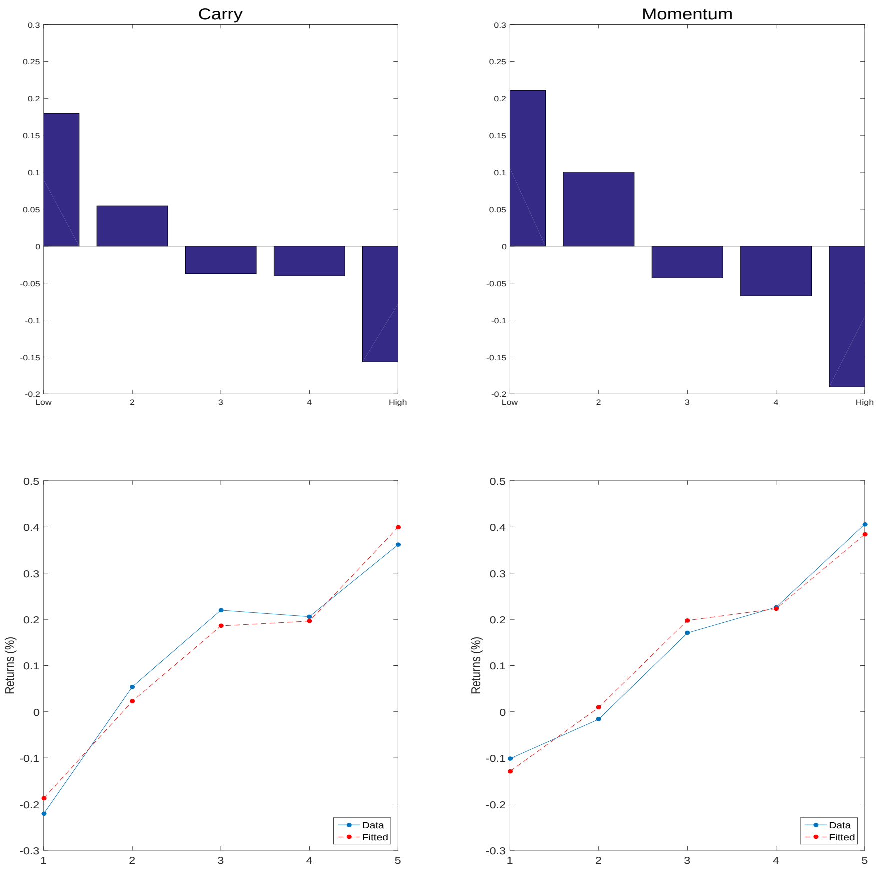
$$\overline{rx}^i = \hat{\beta}_{DOL}^i \lambda_{DOL} + \hat{\beta}_{MPU}^i \lambda_{MPU} + \eta^i, \tag{2.3.2}$$

where the left-hand side is the unconditional mean of portfolio excess returns, and the first-stage estimated betas are used as the explanatory variables on the right-hand side. λ_{DOL} and λ_{MPU} are the risk prices per unit of dollar factor beta and MPU beta. Note that I do not add the intercept at the second stage regression due to the inclusion of the dollar factor (see e.g., Menkhoff et al., 2012a).

The rest columns of Table 2.2 report the outcomes of first-stage time-series regression, where the standard errors of estimated betas are based on Newey and West (1987) with optimal lag selection following Andrews (1991). For both types of cross-sectional portfolios, while they load similarly on the dollar factor, their exposures to u_t^{MPU} decrease monotonically from the bottom to the top portfolios, which are also plotted in the upper panel of Figure 2.2. In fact, the magnitudes of high-minus-low beta spreads are similar and also statistically significant at the 5% level. Obtaining a significant spread in betas is a pivotal check on whether the factor is priced following Kan and Zhang (1999) and Burnside (2011). The monotonic relations are statistically justified via the monotonicity test on betas following Patton and Timmermann (2010), where the p-values are reported and based on the null hypothesis that the betas are monotonically decreasing. The first-stage evidence hence sheds light on the potentially unified explanation of the currency carry and momentum returns by their exposures to the risk of US MPU.

Figure 2.2. MPU **betas and pricing error plots**

The upper panel plots the sensitivities of carry and momentum portfolio returns to the risk of US monetary policy uncertainty (MPU betas), which are estimated from Equation (2.3.1). The lower panel plots the portfolio mean returns and fitted returns from the asset pricing model, estimated over carry and momentum portfolio separately. The sample period is from January 1985 to August 2017.



After obtaining the betas, the cross-sectional regression (2.3.2) is estimated via OLS. For test on the statistical significance of risk prices, I employ the heteroskedastic and autocorrelation consistent (HAC) standard errors based on Newey and West (1987) with optimal lag selection following Andrews (1991) (NW), as well as those of Shanken (1992) (Sh) that further incorporate the adjustments due to the error-in-variable (EIV) problem of using first-stage estimated betas. To recognize the specific and unified pricing power, I use five carry and five momentum portfolios separately or jointly as testing assets. Panel A of Table 2.3 documents the results. The monotonically decreasing betas and increasing portfolio returns render the negative prices for the US *MPU* risk, with the cross-sectional R^2 of 98%. The large R^2 indicates that exposures to *MPU* risk go a long way in reconciling the returns to FX carry and momentum trade. Meanwhile, the magnitudes of risk prices are similar and significant under both types of standard errors. The results are invariant for the joint cross-section of carry and momentum returns, with the R^2 of 96%. To test for zero pricing errors, I further report the p-values from the χ^2-test as discussed in e.g., Cochrane (2005). The computation of χ^2 statistics are also based on the method of Newey-West (χ^2_{NW}) or Shanken (χ^2_{Sh}). From the table, the null hypothesis that all pricing errors are jointly zero cannot be rejected when separately using the carry and momentum portfolios as testing assets. Qualitatively, the close distance between the average portfolio returns and the fitted returns from Equation (2.3.2) can be found from the lower panel of Figure 2.2.

Table 2.3. Cross-sectional asset pricing test

The table reports the results of asset pricing test for the two-factor model containing the dollar factor and the US *MPU* risk (u_t^{MPU}), or its factor-mimicking portfolio returns ($u_{FMM,t}^{MPU}$). The factor-mimicking portfolio is constructed by projecting u_t^{MPU} on the return space of five carry and five momentum portfolios. Panel A and B display the test results via Fama-MacBeth regression, where I report the estimated risk prices, cross-sectional OLS R^2, the heteroskedastic and autocorrelation consistent (HAC) standard errors based on Newey and West (1987) with optimal lag selection following Andrews (1991) (NW), and the Shanken-adjusted standard errors of Shanken (1992) (Sh). The *p*-values of χ^2-test on the null hypothesis that the pricing errors are jointly zero are also reported. Panel C and D display the test results via the GMM estimation, where I report the estimated factor loadings in the SDF model (2.3.5) by using either the identity matrix (GMM1) and the optimal weight matrix (GMM2) in the estimation. The Newey-West standard errors are in parentheses. I also report the *p*-values from the χ^2-test, and the estimated Hansen-Jagannathan distances and their *p*-values, which are obtained via simulation following Jagannathan and Wang (1996). The testing assets are the carry, momentum or their joint cross-sectional portfolios. The sample period is from January 1985 to August 2017.

	Carry			Momentum			Carry+Momentum		
	Panel A: Fama-MacBeth								
	λ_{DOL}	λ_{MPU}	R^2	λ_{DOL}	λ_{MPU}	R^2	λ_{DOL}	λ_{MPU}	R^2
	0.12	-1.64	0.98	0.14	-1.29	0.98	0.13	-1.42	0.96
(NW)	(0.11)	(0.47)		(0.11)	(0.35)		(0.11)	(0.32)	
(Sh)	(0.11)	(0.90)		(0.11)	(0.57)		(0.11)	(0.56)	
χ^2_{NW}	[0.81]			[0.95]			[0.02]		
χ^2_{Sh}	[0.97]			[0.99]			[0.63]		
	Panel B: Fama-MacBeth using factor-mimicking portfolio								
	λ_{DOL}	λ_{MPU}	R^2	λ_{DOL}	λ_{MPU}	R^2	λ_{DOL}	λ_{MPU}	R^2
	0.12	-0.32	0.98	0.14	-0.25	0.98	0.13	-0.28	0.96
(NW)	(0.11)	(0.07)		(0.11)	(0.07)		(0.11)	(0.05)	
(Sh)	(0.11)	(0.07)		(0.11)	(0.07)		(0.11)	(0.05)	
χ^2_{NW}	[0.81]			[0.95]			[0.02]		
χ^2_{Sh}	[0.83]			[0.95]			[0.03]		
	Panel C: GMM								
	b_{DOL}	b_{MPU}	R^2	b_{DOL}	b_{MPU}	R^2	b_{DOL}	b_{MPU}	R^2
GMM1	2.96	-1.64	0.98	3.30	-1.29	0.98	3.16	-1.42	0.96
s.e.	(4.72)	(0.84)		(4.05)	(0.67)		(4.28)	(0.61)	
GMM2	2.58	-1.75	0.97	3.08	-1.33	0.98	2.44	-1.20	0.91
s.e.	(4.60)	(0.71)		(3.98)	(0.60)		(4.10)	(0.48)	
χ^2-test	[0.95]			[0.97]			[0.54]		
HJ-dist	0.05			0.04			0.22		
	[0.96]			[0.97]			[0.24]		
	Panel D: GMM using factor-mimicking portfolio								
	b_{DOL}	b_{MPU}	R^2	b_{DOL}	b_{MPU}	R^2	b_{DOL}	b_{MPU}	R^2
GMM1	0.03	-0.32	0.98	0.03	-0.25	0.98	0.03	-0.28	0.96
s.e.	(0.03)	(0.09)		(0.03)	(0.07)		(0.03)	(0.06)	
GMM2	0.03	-0.35	0.96	0.03	-0.26	0.98	0.04	-0.28	0.95
s.e.	(0.03)	(0.08)		(0.03)	(0.07)		(0.03)	(0.06)	
χ^2-test	[0.77]			[0.93]			[0.12]		
HJ-dist	0.05			0.04			0.22		
	[0.25]			[0.32]			[0.00]		

However, the US *MPU* risk is a non-traded factor. To mitigate the concern of using such type of factor in the asset pricing test, as widely discussed in e.g., Kan and Zhang (1999), I construct the factor-mimicking portfolio by projecting u_t^{MPU} on ten currency portfolios:

$$u_t^{MPU} = a + b' w_t + \varepsilon_t, \tag{2.3.3}$$

where w_t denotes the vector of month-t excess returns of five carry and five momentum portfolios. The obtained fitted part $b' w_t$ is as follows:

$$\begin{aligned} u_{FMM,t}^{MPU} = & -0.01 rx_{C,t}^1 - 0.07 rx_{C,t}^2 - 0.08 rx_{C,t}^3 - 0.08 rx_{C,t}^4 - 0.10 rx_{C,t}^5 \\ & + 0.12 rx_{M,t}^1 + 0.10 rx_{M,t}^2 + 0.03 rx_{M,t}^3 + 0.06 rx_{M,t}^4 + 0.04 rx_{M,t}^5, \end{aligned} \tag{2.3.4}$$

where $rx_{C,t}^j$ and $rx_{M,t}^j$ denote the excess returns of j-th carry and momentum portfolios. The loadings by the factor-mimicking portfolio roughly match the decreasing *MPU* betas, with the high-minus-low weights of -0.09 and -0.08 respectively among carry and momentum portfolios. The correlation coefficient between the factor-mimicking portfolio returns and u_t^{MPU} is 0.20. Since $u_{FMM,t}^{MPU}$ is now a traded factor, without going through any asset pricing test, the Sharpe ratio of the factor-mimicking portfolio already reflects the market price of *MPU* risk. Its monthly SR is -0.26 with a Newey-West t-statistic of -3.54. The magnitude of SR is even slightly larger than those of carry and momentum strategies, suggesting that the US *MPU* risk explains a bulk of the strategy returns. Then I follow the previous exercises by running the cross-sectional asset pricing test, using $u_{FMM,t}^{MPU}$ instead of u_t^{MPU} as the risk factor. The results are in Panel B of Table 2.3. The main findings are still there with large cross-sectional R^2, but now the risk prices become more significant, thanks to the usage of asset return series as the risk factor that yields more accurate inference. The Shanken t-statistic reach as large as -5.6 when using the joint cross-section of currency portfolios as testing assets.

The two-stage method though is easy to implement, the pre-estimation of *MPU* betas is unfavorable because it introduces the error-in-variable problem when running the cross-sectional test. I thereby employ the Generalized Method of Moments (GMM) to estimate the asset pricing model in one-step directly. The analysis begins with a parametric form for the stochastic discount factor (SDF) that is linear in risk factors:

$$M_{t+1} = 1 - b_{DOL}(DOL_{t+1} - \mu_{DOL}) - b_{MPU}u_{t+1}^{MPU}, \tag{2.3.5}$$

and the Euler equations:

$$E(M_{t+1}RX_{t+1}^{i}) = 0, \tag{2.3.6}$$

where RX_{t+1}^{i} is the excess return of testing asset i. Then I set up the moment conditions as follows:

$$E(g_{t+1}) = E\begin{bmatrix} (1 - b_{DOL}(DOL_{t+1} - \mu_{DOL}) - b_{MPU}u_{t+1}^{MPU})RX_{t+1}^{i} \\ DOL_{t+1} - \mu_{DOL} \\ Cov([DOL_{t+1}, u_{t+1}^{MPU}]') - \Sigma_{DOL,MPU} \end{bmatrix} = 0. \tag{2.3.7}$$

These moment conditions allow for the joint inference on the parameters of SD-F and risk factors. In Panel C and D of Table 2.3, I test the pricing power of u_t^{MPU} as well as its factor-mimicking portfolio returns via GMM. The estimation is carried out by using either the prespecified identity matrix (GMM1) or the optimal weight matrix (GMM2). To test for zero pricing errors, I display the p-values from the χ^2-test. Further to measure the model misspecification, I also report the Hansen-Jagannathan distance of Hansen and Jagannathan (1997), where the simulation based p-values following Jagannathan and Wang (1996) are in brackets. I find that while the first-stage GMM estimation delivers the identical R^2 with that from the Fama-MacBeth regression, the GMM with optimal weight matrix yields similar results. The risk prices are significant, and the cross-sectional R^2 are still above 90%. The null hypothesis of zero pricing errors cannot be rejected. In fact, the Hansen-Jagannathan distances are also very small and not significantly different from zero.

2.3.2 Other proxies for the US monetary policy uncertainty

To avoid the concern of data-mining, instead of the BBD MPU index that tilts towards the subjective uncertainty, in this subsection I examine the results by using the realized uncertainty measures of the US MPU. Specifically, I compute the monthly realized variance of 1-year and 10-year constant maturity Treasury yield from the daily data. The choice of maturities guarantees that I evaluate the robustness of results concerning the volatility of both the short- and long-horizon interest rate. Figure A.1 plots these two series of realized variance. Then I obtain the candidate risk factors by extracting the innovations from the commonly used AR(1) model.

The results from using the realized variance of interest rate (IRV) resemble those based on the news-based index, as shown in Table 2.4. The portfolios' IRV betas decrease monotonically from low to high carry or momentum portfolio. The high-minus-low beta spreads remain significant for both 1-year and 10-year interest rate uncertainty. The lower part of each panel reports the results of cross-sectional asset pricing test using the Fama-MacBeth method. I find that although the explanatory power of IRV risk on the joint cross-section of carry and momentum returns now drops to 84% (1Y) and 90% (10Y) respectively, the risk prices are still negative and significant. Hence the novel empirical findings do not rely on the specific choice of measures for the US MPU.

2.4 Inspecting the mechanism

In this section, I discuss the reason why exposures to the US MPU risk jointly explain the cross-section of FX carry and momentum returns. To streamline the analysis, I study and extend an intermediary-based exchange rate model of Mueller et al. (2017) and more broadly Gabaix and Maggiori (2015). In the model, the financial intermediary, called the *financier*, bears the excess currency supply resulting from the imbalanced cross-border asset flows between the US and foreign countries. The equilibrium currency risk premium is determined jointly with intermediary's cur-

Table 2.4. Asset pricing performance using the realized variance of US interest rate

The table reports the results of asset pricing test for the two-factor model containing the dollar factor and the US *MPU* risk, which is obtained by using the shock to the interest rate realized variance (IRV) instead of BBD *MPU* index. The monthly realized variance is computed using daily 1-year and 10-year US Treasury yields. In each panel, I first report the estimated *IRV* betas of carry and momentum portfolios, their Newey-West standard errors and the p-values of two types of monotonic relation (MR) test as in Table 3.2. Then I display the results of asset pricing test via the Fama-MacBeth regression, where I report the estimated risk prices, cross-sectional OLS R^2, the heteroskedastic and autocorrelation consistent (HAC) standard errors based on Newey and West (1987) with optimal lag selection following Andrews (1991) (NW), and the Shanken-adjusted standard errors of Shanken (1992) (Sh). The p-values of χ^2-test on the null hypothesis that the pricing errors are jointly zero are also reported. The testing assets are the carry, momentum or their joint cross-sectional portfolios. The sample period is from January 1985 to August 2017.

	Panel A: 1-year Treasury yields						
	L	2	3	4	H	HML	MR
β^C_{IRV}	0.21	0.06	-0.01	0.03	-0.29	-0.50	[1.00]
	(0.07)	(0.05)	(0.05)	(0.06)	(0.11)	(-0.16)	(0.98)
β^M_{IRV}	0.12	0.14	-0.01	-0.02	-0.21	-0.33	[1.00]
	(0.14)	(0.04)	(0.13)	(0.05)	(0.08)	(0.20)	(0.92)
λ^C_{IRV}	-1.02	R^2	0.81	χ^2_{NW}	[0.07]		
(NW)	(0.33)			χ^2_{Sh}	[0.32]		
(Sh)	(0.47)						
λ^M_{IRV}	-1.38	R^2	0.92	χ^2_{NW}	[0.58]		
(NW)	(0.37)			χ^2_{Sh}	[0.88]		
(Sh)	(0.62)						
λ^{C+M}_{IRV}	-1.15	R^2	0.84	χ^2_{NW}	[0.02]		
(NW)	(0.29)			χ^2_{Sh}	[0.46]		
(Sh)	(0.43)						
	Panel B: 10-year Treasury yields						
	L	2	3	4	H	HML	MR
β^C_{IRV}	0.19	0.06	-0.06	0.03	-0.22	-0.41	[1.00]
	(0.08)	(0.05)	(0.06)	(0.06)	(0.13)	(0.20)	(0.97)
β^M_{IRV}	0.18	0.07	-0.05	-0.03	-0.17	-0.35	[1.00]
	(0.10)	(0.07)	(0.10)	(0.05)	(0.12)	(-0.20)	(0.93)
λ^C_{IRV}	-1.26	R^2	0.87	χ^2_{NW}	[0.14]		
(NW)	(0.38)			χ^2_{Sh}	[0.55]		
(Sh)	(0.61)						
λ^M_{IRV}	-1.51	R^2	0.95	χ^2_{NW}	[0.55]		
(NW)	(0.43)			χ^2_{Sh}	[0.89]		
(Sh)	(0.77)						
λ^{C+M}_{IRV}	-1.37	R^2	0.90	χ^2_{NW}	[0.03]		
(NW)	(0.33)			χ^2_{Sh}	[0.64]		
(Sh)	(0.55)						

rency holding, in the presence of her financial frictions. Importantly, facing foreign currencies with different attributes, the risk-taking by the financier differs, which then translates to different risk premia and responses to the US *MPU* shocks. More explicitly at the cross-section of carry, the foreign currency with higher interest rate is more attractive to hold (compared with USD) because of the yield benefit, but the low interest rate currency tends to be shorted. Higher *MPU* tightens the financial constraints and forces the financier to cut both long and short positions, thereby decreasing the return to high interest rate currency and increasing that to low interest rate currency.

At the cross-section of currency momentum, the long-short decision also presents. I first provide novel evidence that the loser portfolio is populated by countries with higher expected demand for US asset (equity). Embedding this fact into the theory, when the financier expects that there will be a higher supply of foreign currency, arising from such demand, then the financier is more willing to short-sell the foreign currency today to benefit from potential depreciation. Higher *MPU* then increases the return to depreciated currency. The opposite holds for the appreciated currency against USD.

Since the theoretical mechanism builds on the large and unique impact of US *MPU* on the tightness of financial constraints, I provide evidence to show that the US *MPU* risk indeed predicts the risk-taking activity of the intermediary sector who accommodates cross-border flows. Meanwhile, I follow recent literature (e.g., Adrian et al., 2014; He et al., 2017) by examining the pricing of *MPU* risk across asset classes. I find that the US *MPU* risk is also negatively priced in the cross-section of bonds, stocks, and options.

2.4.1 Theoretical results

There are two periods with $t = 0, 1$; and in the economy there are two countries, United States and a foreign country, each with its currency USD and FCU.[6] The

[6] Since the cross-sectional carry or momentum portfolios should only differ in terms of the lagged interest rate differentials or realized returns, I adopt a parsimonious setting with one country but

household in the US (foreign country) has the demand f_t (d_t) for assets denominated in FCU (USD). Both quantities are nominal and denominated in their domestic currencies, and I treat them as exogenous variables throughout the analysis.[7] f_t and d_t are random and in particular, f_t is drawn at t from the distribution $F(\cdot)$ with the support $[\underline{f}, \bar{f}]$. The assumption on the distribution of d_t will be clear later. At $t = 0$, there are non-defaultable bonds issued in each country under local currencies, which mature at $t = 1$. R (R^*) represents the gross interest rate in the US (foreign country) between $t = 0$ and $t = 1$, where R^* is fixed but R only becomes known at $t = 1$.[8] The mean and standard deviation of the distribution of R are denoted as $\bar{R}$ and σ, both parameters are known at $t = 0$. From the definition, σ captures the US monetary policy uncertainty.[9] All stochastic quantities are mutually independent.

At $t = 0$, there is a representative financial intermediary, which is called the *financier*. She is risk-neutral and can buy or sell the domestic bonds of both countries. Although households in each country have demand for foreign assets, they can only trade the foreign currencies with the financier, i.e., the market is incomplete. As in Gabaix and Maggiori (2015), the role of the financier is to intermediate the currency demand of households across countries and absorbs the resulting imbalance. The financier enters the market with no initial capital: she takes the position of $-Q$ in USD funded by Q/e_0 units of FCU, where the exchange rate e_t is defined as the unit of USD per unit of FCU at time t. The payoff function of the financier at $t = 1$ is

$$V_1 = (\frac{e_1}{e_0}R^* - R)Q. \tag{2.4.1}$$

Moreover, the financier has limited risk bearing capacity. She commits to the Value-at-Risk (VaR) constraint when taking currency positions. The objective at

focus on the comparative statics of the equilibrium with respect to different parameters governing FX carry and momentum.

[7]The imperfect substitutability is a source of demand for foreign assets in addition to home assets.

[8]It is straightforward to make the interest rate predetermined, or make the bond risk-free as in Mueller et al. (2017) via a three-period model. However, that complicates the analysis without changing the economic intuition.

[9]In the Internet Appendix, I develop a model where the US monetary policy uncertainty is introduced as the *ambiguity*. That is, even the distribution of R itself becomes unknown. All subsequent implications are preserved.

$t = 0$ for the financier is thus written as

$$\begin{aligned} \max_{Q} \quad & E_0[V_1], \\ s.t. \quad & P_0(V_1 \leq 0) \leq \alpha, \end{aligned} \tag{2.4.2}$$

where α is the VaR limit. As the financier absorbs larger position, the VaR constraint becomes more binding, this effectively restricts the risk-taking behavior of the intermediary. The equilibrium of the economy is then defined as the financier chooses allocation Q to solve the objective, and the exchange rate adjusts such that the market clears at each period:

$$d_0 e_0 - f_0 - Q \quad = 0, \tag{2.4.3}$$

$$d_1 e_1 - f_1 + RQ \quad = 0. \tag{2.4.4}$$

Since both f_1 and d_1 are unknown at $t = 0$, I let the financier first estimate the conditional expectation of d_1/d_0; then she solves the optimal portfolio choice problem by directly embedding such forecast. This assumption greatly simplifies the closed-form model solutions, because now the financier only treats f_1 as stochastic when making decisions. The equilibrium allocation and currency risk premium at $t = 0$, together with the comparative statics with respect to the US *MPU* σ are detailed in the following proposition.

PROPOSITION 1. *Define the distribution function of $R^{-1} f_1$ as $H(\cdot)$, and denote $g = E_0[d_1/d_0]$ as the expected growth of foreign demand for US asset. Suppose α is small enough, then the equilibrium currency demand of the financier is*

$$Q = \begin{cases} \frac{H^{-1}(\alpha) R^* - g f_0}{R^* + g}, & Q > 0, \\ \frac{H^{-1}(1-\alpha) R^* - g f_0}{R^* + g}, & Q < 0. \end{cases} \tag{2.4.5}$$

Define the excess return of borrowing USD and investing in the foreign currency as

$\phi = \frac{e_1 R^*}{e_0 R} - 1$, *then the currency risk premium is*

$$E_0[\phi] = \begin{cases} \frac{(E_0[R^{-1} f_1] - H^{-1}(\alpha))(R^* + g)}{(H^{-1}(\alpha) + f_0) g} > 0, & Q > 0, \\ \frac{(E_0[R^{-1} f_1] - H^{-1}(1-\alpha))(R^* + g)}{(H^{-1}(\alpha) + f_0) g} < 0, & Q < 0. \end{cases} \quad (2.4.6)$$

When Q is positive (negative), Q decreases (increases) and $E_0[\phi]$ increases (decreases) with respect to σ.

The intermediary requires positive risk premium whenever she bears the position of foreign currency by borrowing the USD, given that α is small. Facing higher US *MPU*, the financier has to reduce the currency holding, which translates to lower currency return but higher risk premium. The same mechanism holds when the intermediary borrows FCU and holds USD, from which the return sensitivity to the US *MPU* shock becomes positive.

Regarding the cross-section of carry and momentum, if high interest rate or appreciated currency is held, and that with low interest rate or depreciation is shorted by the intermediary, then the model predictions align well with the empirical findings in Table 3.2. That is, the FX carry and momentum is profitable and the high-minus-low *MPU* beta spreads are negative. Whether the intermediary indeed acts in such a way relies on their demand equation (2.4.5). For two variables characterizing the foreign currency: if R^* is high or g is low, *ceteris paribus*, the intermediary is willing to hold the foreign currency by borrowing USD, and vice versa. The intuition is that higher foreign interest rate means higher investment yield, and expected lower foreign demand for US equity means a lower supply of foreign currency that tends to appreciate the foreign currency in the future.

While the use of R^* to capture the cross-section of carry is straightforward, it is not obvious why currency momentum is negatively related to g. That is, why realized currency depreciation against USD *predicts* more purchases of US asset at the cross-section? I thereby first provide empirical evidence to establish this link. The monthly country-level foreign purchase of US equity, with data available from the Treasury International Capital (TIC) system, is a direct empirical counterpart to d_t (see e.g., Hau and Rey, 2005; Dumas et al., 2016).[10] I then test the *cross-sectional predictability* via two standard methods: portfolio formation and currency-level Fama-MacBeth regression. To ensure robustness of the findings, I choose different window sizes to compute currency realized excess returns, and different forecasting horizons to evaluate the predictability. The left part of each panel in Table 2.5 reports the portfolio-level results. By construction, they are simply the currency momentum portfolios. I find that when moving from the loser to the winner portfolio, the future growth of foreign purchases of US equity declines almost monotonically. The high-minus-low differences are negative and most of them are significant at least at 10% level. Switching to the right panel, I report the average slope coefficient and R^2 from the following Fama-MacBeth cross-sectional regression, under different j and h:

$$\log d_{t+h}^i - \log d_t^i = b_{0,t} + b_t rx_{t-j:t}^i + \varepsilon_{t+1}^i, \qquad i = 1, 2, \cdots N_t, \tag{2.4.7}$$

where N_t is the number of countries with available data at month-t. The currency-level results also point to the negative and significant predictive power of currency returns on future flow changes. The effects are even stronger under many situations, with the Newey-West t-statistic as large as -3.10.

The results presented in the table are new to the literature on currency momentum. To understand them, I borrow some insights from the literature on international capital flows, and in particular the studies on "return-chasing" behavior (see e.g., Bohn and Tesar, 1996; Froot et al., 2001; Dumas et al., 2016). According to the simple ICAPM framework of Bohn and Tesar (1996), the investor adjusts portfolio weights when the expectations of returns are revised over time. Since foreign investors care about the profits denominated in the local currency, they treat the returns from US equity and currency as a bundle. For those in the country whose

[10] However, the raw data is denominated in USD. To match the definition of d_t and change the denomination to local currency, I multiply them by within-month average FX rates (computed from daily mid-spot rates).

Table 2.5. Cross-sectional predictability of equity flows by currency returns
The table reports the results of using currency excess returns to predict future bilateral equity flows. For each country, $rx_{t-j:t}$ is the currency excess return (vis-à-vis USD) between month $t-j$ to t, and $\log d_{t+h} - \log d_t$ is the log change of country's gross purchase of US equity between month t to $t+h$, where the forecasting horizon h ranges from one- to three-month. Panel A to C correspond to the results for j = 1, 2 and 3. The left part of each panel reports the time series average of $\log d_{t+h} - \log d_t$ for portfolios formed by sorting on currency excess return $rx_{t-j:t}$ at the end of month-t, and the right part displays the average slope coefficients from the currency-level Fama-MacBeth cross-sectional regression (2.4.7). Reported R^2 is the time-series average of cross-sectional R^2 from the regressions. All t-statistics are reported in the parentheses and based on the standard errors of Newey and West (1987) with the optimal lag selection of Andrews (1991). The sample period is from January 1985 to August 2017.

	Portfolio approach						Fama-MacBeth	
	L	2	3	4	H	HML	b	$R^2(\%)$
Panel A: $rx_{t-1:t}$ on $\log d_{t+h} - \log d_t$								
$h=1$	2.09	1.18	1.57	2.34	0.17	-1.92	-0.31	4.76
(t)	(1.80)	(0.89)	(1.19)	(2.11)	(0.16)	(-1.37)	(-1.72)	
$h=2$	2.99	0.92	0.67	0.60	0.39	-2.69	-0.75	4.65
(t)	(3.82)	(0.82)	(0.80)	(0.64)	(0.50)	(-2.96)	(-2.98)	
$h=3$	2.19	1.11	1.05	1.33	0.74	-1.46	-0.62	4.64
(t)	(3.83)	(1.51)	(1.55)	(2.13)	(1.27)	(-2.89)	(-2.65)	
Panel B: $rx_{t-2:t}$ on $\log d_{t+h} - \log d_t$								
$h=1$	3.17	1.14	2.22	1.58	-0.24	-3.42	-0.33	4.94
(t)	(2.75)	(0.80)	(1.86)	(1.46)	(-0.25)	(-2.58)	(-2.66)	
$h=2$	4.94	2.25	4.08	1.32	1.21	-3.73	-0.46	4.43
(t)	(2.99)	(1.14)	(2.63)	(0.80)	(0.77)	(-2.07)	(-3.10)	
$h=3$	5.89	4.23	4.43	3.16	1.95	-3.94	-0.48	4.71
(t)	(3.23)	(1.76)	(2.35)	(1.67)	(1.09)	(-2.33)	(-3.04)	
Panel C: $rx_{t-3:t}$ on $\log d_{t+h} - \log d_t$								
$h=1$	1.92	2.05	1.99	1.43	0.17	-1.75	-0.16	5.13
(t)	(1.88)	(1.53)	(1.74)	(1.25)	(0.19)	(-1.52)	(-1.64)	
$h=2$	2.05	2.62	0.65	0.96	0.73	-1.32	-0.34	4.29
(t)	(2.67)	(2.72)	(0.77)	(1.16)	(0.95)	(-1.50)	(-2.97)	
$h=3$	1.40	2.42	0.73	0.45	1.18	-0.22	-0.37	4.62
(t)	(2.93)	(3.13)	(1.14)	(0.72)	(1.96)	(-0.97)	(-2.71)	

currency depreciates more against USD, they realize higher returns from the US stock market. As a result, their beliefs on returns are pushed up, which triggers further purchases of US equity.[11]

Embedding the evidence into the model, I characterize the currency momentum with the parameter g, i.e., the winner portfolio is accompanied with the lowest expected growth of foreign purchases of US equity. From the equilibrium described by (2.4.5), when g is sufficiently low, the financial intermediary chooses to hold the foreign currency. The equilibrium is such that the winner currency has positive risk premium and negative MPU beta; and by the same logic, because the loser currency is shorted, it has negative risk premium and positive MPU beta. These implications are summarized as follows:

COROLLARY 1. *Currency carry and momentum strategies are profitable, and their high-minus-low spreads in betas to the US MPU risk are negative.*

2.4.2 Do US *MPU* shocks affect the intermediary?

In this subsection, I test empirically whether the US MPU shocks impact the financial frictions of the financier. Motivated by Obstfeld (2012), who emphasizes the link between fluctuations of gross flows and financial sectors, I propose to relate the tightness of intermediary constraints to the *changes* in gross equity flows between *all* foreign countries and the US, with data again from the TIC system. These flows are collected mainly from the brokers and dealers involved in the cross-border transactions.[12] The primary reason for using this measure is because shocks to intermediary constraints should drive these flows between public investors and the financier. Also, relying on such transaction data circumvents the tricky identification of specific intermediaries (see e.g. Baron and Muir, 2018). The global measure

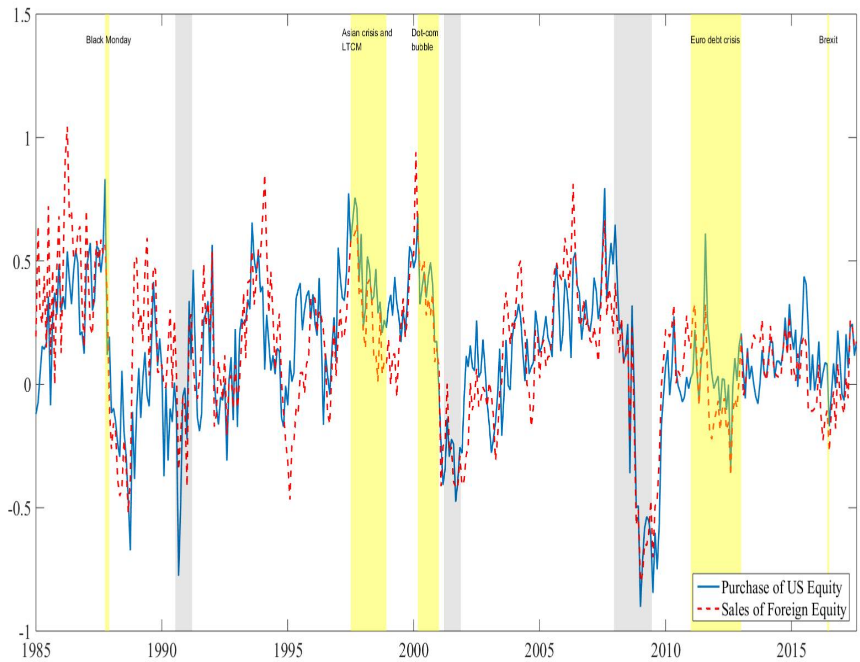
[11] See more theoretical discussions in e.g., Brennan and Cao (1997) and Dumas et al. (2016).

[12] Reporting is legally required if their monthly transactions are above \$50 million during the reporting month. While the data of US purchases of all foreign equity are readily available from the TIC system, I construct the foreign purchases of US equity as the cross-sectional average of purchases by all available foreign countries (excluding the transactions with amount less than \$10 million).

further removes idiosyncratic drivers of equity flows by different foreign countries, which facilitates the quantifying of the systematic risk related to the intermediary sector. Figure 2.3 then plots the year-over-year log changes in these equity flows, together with the usual NBER recession periods (gray bars) and the periods with significant financial turmoil but no US recession (yellow bars).[13] Flow growth significantly drops during the distress periods when the constraint of intermediary is more likely to bind, and the fluctuations of inflows and outflows against the US show substantial co-movement. The interesting cyclical property and commonality suggest that the flow changes indeed measure the tightness of intermediary constraints to some extent.

Figure 2.3. Fluctuations of bilateral equity flows

The figure plots the year-over-year log change in the foreign purchases of US equity from US residents (blue solid line) and the sales of foreign equity to US residents (red dashed line), by all foreign countries. The gray bars denote the NBER recession periods, and the yellow bars denote the periods with significant financial turmoil but without US recession. The sample period is from January 1985 to August 2017.



[13]Studying the year-over-year change mitigates the concern of potential seasonality in cross-border security trading.

In addition to the supply shocks from the intermediary, however, the flow changes can also reflect the demand shocks from public equity investors. These shocks may be further driven by changes in risk aversion or market news, instead of the change in the US *MPU*. Fortunately, since my task is to evaluate whether the US *MPU* risk impacts the constraint of intermediary, explicit separation of the demand and supply shocks is not necessary as long as the demand effects can be controlled.[14] I thus consider the following predictive regression to evaluate the impact of US *MPU* risk on intermediary constraints:

$$\Delta Global_{t+1} = \alpha + \rho \Delta Global_t + \beta u_t^{MPU} + \gamma X_t + \varepsilon_{t+1}. \tag{2.4.8}$$

$\Delta Global_{t+1}$ represents the growth rate of equity inflows or outflows against the US as plotted in Figure 2.3. The term involving X_t seeks to control for the flow changes arising from the demand shock to equity investing. Also because the growth rate shows moderate persistence, I add the lagged value in the regression. If higher US *MPU* tightens the financial constraint, we should expect that the growth of equity inflows and outflows *both* drop, i.e., $\beta < 0$.

To choose variables used as controls for the demand effect, I draw from the literature on the ICAPM that serves as the workhorse model for the portfolio choice problem. The model relates the demand for equity with the return volatility and states driving the investment opportunity set (Chacko and Viceira, 2005). Although the ICAPM does not explicitly points out which state affects the opportunity set, the empirical literature typically uses the variable that predicts aggregate returns (see e.g., Maio and Santa-Clara, 2012). I hereby use 16 predictors for the US equity market surveyed in Welch and Goyal (2007) as controls when studying the foreign demand for US equity. Nevertheless, the US-based variables may not be important controls to capture the demand changes on the US purchases of foreign equity. Hence I further use the powerful predictors of returns to stock markets outside of

[14] Separation of demand and supply shocks requires nontrivial assumptions and econometric techniques (see e.g., Chen et al., 2018). It is beyond the scope of this paper to discuss how to achieve that from the bilateral equity flows.

US, including the lagged US market return as in Rapach et al. (2013), and the return variance constructed from stock markets outside the US.

Figure 2.4 displays the Newey-West t-statistics of estimated γ and β in Equation (2.4.8). On the demand side, as shown in the upper panel, the stock market variance is the most important factor for both inflows and outflows. The results are in line with the usual implication from the ICAPM: higher return volatility dampens the investor's demand for stocks. More importantly, estimates of β are indeed negative under all controls. The coefficients are significant when using the growth of global purchases of US equity as the dependent variables.[15] Therefore, the impact of US *MPU* risk on the intermediary constraints is supported by the micro-level data.

2.4.3 Pricing other asset classes

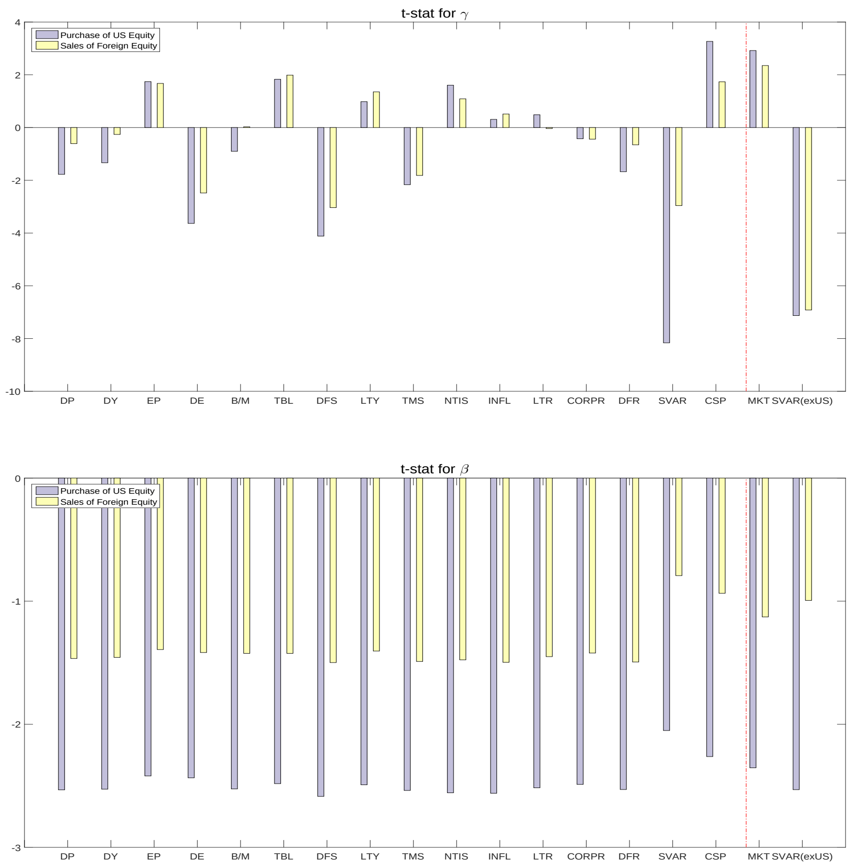
Another important dimension for the intermediary-based story is whether the US *MPU* risk also prices other asset classes, because the financial intermediary is likely to be the marginal investor in many financial markets (He et al., 2017). Obtaining consistent risk price estimates from other assets helps mitigate the concern of data-snooping, or spurious findings due to the strong factor structure of particular testing assets, following the prescription of Lewellen et al. (2010). To this end, I augment the FX10 (5 carry and 5 momentum) portfolios with the those covering the bonds, options, and stocks. Specifically, I consider 10 US corporate bond portfolios sorted on the yield spread from Nozawa (2017); 6 sovereign bond portfolios sorted on bond beta and credit rating from Borri and Verdelhan (2015); 18 portfolios of S&P 500 index options sorted on moneyness and maturity from Constantinides et al. (2013); Fama-French 25 portfolios sorted on size and momentum, and 25 portfolios sorted on size and book-to-market.

For the asset pricing test, due to the inclusion of many non-FX assets, I use the single-factor model with only the *MPU* risk, and I add constant at the second stage cross-sectional regression to account for non-zero beta rate following He

[15]Regression results are similar if using the month-to-month log changes in equity flows, as plotted in Figure A.2.

Figure 2.4. Impact on the financial frictions of intermediary sector

The figure plots the t-statistics for γ and β estimated from Equation (2.4.8). The control variables include 16 US return predictors from Welch and Goyal (2007), the international stock return predictor from Rapach et al. (2013), and the return variance constructed from stock markets outside the US. The red vertical line separates the states governing the demand for US equity (to the left) and the demand for foreign equity (to the right). The sample period is from January 1985 to August 2017.



et al. (2017). Figure 2.5 displays the scatter plots between average portfolio excess returns and the fitted returns. The results show that the US *MPU* risk does reasonably well in capturing the return spreads across currencies and other assets. The cross-sectional R^2 ranges from 59% (FX10+Sovereign bond) to 82% (FX10+Size-momentum). Furthermore, Table 2.6 reports the estimated prices for the US *MPU* risk and the zero-beta rates from each group of testing assets. I find that all prices for *MPU* risk are negative and significant. On the other hand, the estimated zero-beta rates are insignificant, suggesting that the magnitudes of pricing errors are not large. These results fit well the theory that higher US *MPU* tightens the risk-bearing capacity of the financial intermediary, which should transmit to negative prices of risk among many asset classes.

Figure 2.5. Pricing error plots for currency carry, momentum and other assets

The figure contains the scatter plots between realized average portfolio excess returns and the fitted excess returns from the one-factor asset pricing model with the US *MPU* risk. Each panel represents the result of augmenting the testing assets of FX10 (carry and momentum) portfolios by a specific asset class. The intercept is added when running the second-stage cross-sectional regression, similar to the role of the dollar factor in the baseline setting. Due to data availability of other asset classes, the sample period is from January 1985 to December 2012.

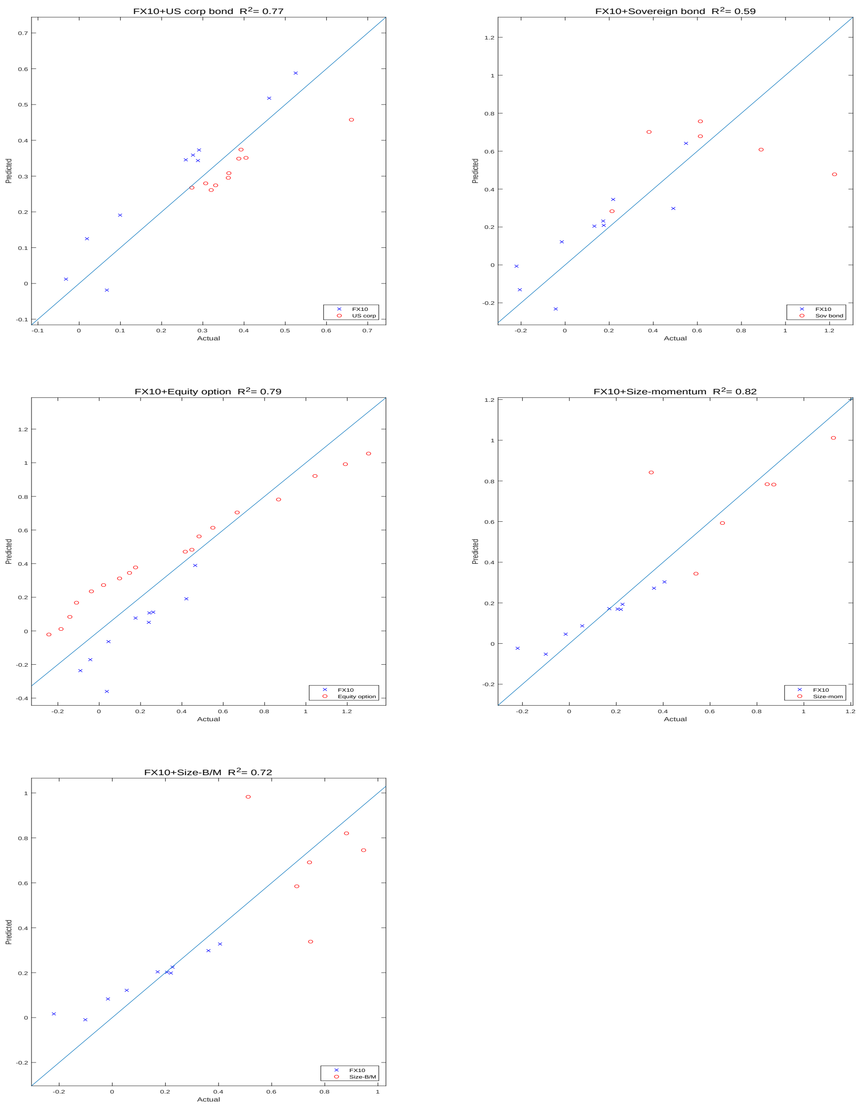


Table 2.6. Pricing the joint cross-section of FX and other asset classes

The table reports the results of asset pricing test using the single factor asset pricing model with the US *MPU* risk (u_t^{MPU}). The augmented testing assets consist of FX carry and momentum portfolios (FX10) and portfolios from other asset classes. The test is done via the Fama-MacBeth regression, where I report the estimated risk prices, cross-sectional OLS R^2, the heteroskedastic and autocorrelation consistent (HAC) standard errors based on Newey and West (1987) with optimal lag selection following Andrews (1991) (NW), and the Shanken-adjusted standard errors of Shanken (1992) (Sh). I add the constant in the second-stage regression, similar to the role of the dollar factor in the baseline setting. Due to data availability of other asset classes, the sample period is from January 1985 to December 2012.

	λ_0	λ_{MPU}	R^2
FX10+US Corp bond	0.27	-1.46	0.77
(NW)	(0.08)	(0.28)	
(Sh)	(0.13)	(0.48)	
FX10+Sovereign bond	0.38	-1.90	0.59
(NW)	(0.15)	(0.52)	
(Sh)	(0.31)	(1.07)	
FX10+Equity option	0.01	-1.40	0.79
(NW)	(0.13)	(0.39)	
(Sh)	(0.21)	(0.65)	
FX10+Size-momentum	0.14	-0.88	0.82
(NW)	(0.10)	(0.30)	
(Sh)	(0.14)	(0.40)	
FX10+Size-B/M	0.17	-0.84	0.72
(NW)	(0.10)	(0.31)	
(Sh)	(0.13)	(0.40)	

2.5 Robustness Checks

In this section, I carry out a battery of robustness checks to ensure that the main empirical findings are invariant to alternative setups or implementations. Some of the results are in the Internet Appendix.

2.5.1 Asset pricing test including other factors

It is important to ensure that the new findings are unrelated to existing explanations. I thus test whether the inclusion of other risk factors can attenuate the explanatory power of *MPU* risk by running the asset pricing test with the dollar factor, US *MPU* risk, and the control variables. I consider two types of controls, where the first type contains other measures of financial frictions, and the second includes commonly used currency risk factors. The inclusion of the former type is necessary to ensure that the usefulness of *MPU* risk is not subsumed by other measures of financial frictions, given their similar roles in theory.

To be more specific, I consider five measures of financial frictions: VIX and TED spread of Brunnermeier et al. (2008), bond liquidity factor of Fontaine and Garcia (2011), betting against beta factor of Frazzini and Pedersen (2014), and intermediary's capital ratio of He et al. (2017).[16] For currency risk factors, I use the global FX volatility of Menkhoff et al. (2012a), FX liquidity factor of Karnaukh et al. (2015), the recently proposed global equity correlation of Bae and Elkamhi (2017),[17] and the slope factors (high-minus-low returns) from carry and momentum portfolios. Table 2.7 reports the results of asset pricing test of the three-factor model via Fama-MacBeth regression, by using the joint cross-section of carry and momentum portfolios as testing assets. For comparison, I also display the outcomes from a model without using the *MPU* risk. While these competing risk factors fail to jointly reconcile the carry and momentum returns, as manifested by the low R^2, the explanatory power of US *MPU* risk is unaffected by adding in those controls. Moreover, despite the significant risk prices for many control variables, partly due to the success of explaining carry returns, their magnitudes of risk prices decrease substantially after adding in the US *MPU* risk. Thus the evidence removes the concern that the information of the US *MPU* risk is subsumed by other risk factors.

[16] Since the leverage ratio of Adrian et al. (2014) is only available at the quarterly frequency, and He et al. (2017) show that their factor is the reciprocal of that of Adrian et al. (2014). I mainly focus on the monthly factor of He et al. (2017). Quarterly results using the leverage ratio are similar and available upon request.

[17] The replicated series is plotted in Figure A.3.

Table 2.7. Robustness: Pricing power of *MPU* under controls

The table reports the results of asset pricing test on the joint cross-section of currency carry and momentum portfolios, by including other control variables in addition to US *MPU* risk. Panel A contains the controls measuring the financial frictions: VIX and TED spread, the bond liquidity factor of Fontaine and Garcia (2011), betting against beta factor of Frazzini and Pedersen (2014), intermediary's capital ratio of He et al. (2017). Panel B contains the currency risk factors: the global FX volatility of Menkhoff et al. (2012a), FX liquidity factor of Karnaukh et al. (2015), global equity correlation of Bae and Elkamhi (2017), and the high-minus-low returns of carry and momentum portfolios. The test is done via Fama-MacBeth regression, where I report the estimated risk prices, cross-sectional OLS R^2, the heteroskedastic and autocorrelation consistent (HAC) standard errors based on Newey and West (1987) with optimal lag selection following Andrews (1991) (NW), and the Shanken-adjusted standard errors of Shanken (1992) (Sh). The *p*-values of χ^2-test on the null hypothesis that the pricing errors are jointly zero are also reported. The sample period is from January 1985 to August 2017.

Panel A: Other measures of financial frictions										
X	VIX		TED		Bond liquidity		BAB		Capital ratio	
λ_X	-0.68	-0.46	-1.84	-0.12	-0.90	-0.24	1.76	-0.24	0.49	0.28
(NW)	(0.22)	(0.21)	(0.49)	(0.57)	(0.40)	(0.35)	(0.56)	(0.43)	(0.23)	(0.23)
(Sh)	(0.27)	(0.34)	(1.01)	(0.95)	(0.53)	(0.57)	(1.13)	(0.79)	(0.25)	(0.33)
λ_{MPU}		-1.26		-1.35		-1.27		-1.48		-1.11
(NW)		(0.29)		(0.33)		(0.30)		(0.33)		(0.32)
(Sh)		(0.47)		(0.56)		(0.47)		(0.60)		(0.47)
R^2	0.33	0.95	0.53	0.92	0.09	0.91	0.32	0.97	0.37	0.94
χ^2_{NW}	[0.00]	[0.04]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.19]
χ^2_{Sh}	[0.02]	[0.58]	[0.73]	[0.50]	[0.02]	[0.34]	[0.37]	[0.61]	[0.05]	[0.70]
Panel B: Other currency risk factors										
X	FX Vol		FX liquidity		GEC		HML_{carry}		HML_{mom}	
λ_X	-0.46	-0.17	-0.74	-0.07	-0.81	-0.35	0.19	0.21	0.19	0.17
(NW)	(0.17)	(0.17)	(0.35)	(0.34)	(0.37)	(0.37)	(0.05)	(0.05)	(0.05)	(0.05)
(Sh)	(0.19)	(0.28)	(0.44)	(0.58)	(0.47)	(0.63)	(0.05)	(0.06)	(0.05)	(0.05)
λ_{MPU}		-1.36		-1.38		-1.42		-1.34		-1.60
(NW)		(0.33)		(0.32)		(0.33)		(0.36)		(0.50)
(Sh)		(0.55)		(0.55)		(0.56)		(0.60)		(0.94)
R^2	0.32	0.97	0.20	0.97	0.26	0.97	0.45	0.97	0.55	0.97
χ^2_{NW}	[0.00]	[0.01]	[0.00]	[0.01]	[0.00]	[0.01]	[0.00]	[0.02]	[0.00]	[0.01]
χ^2_{Sh}	[0.00]	[0.53]	[0.00]	[0.54]	[0.01]	[0.52]	[0.00]	[0.56]	[0.00]	[0.58]

2.5.2 Time-varying *MPU* betas

In the baseline asset pricing test, the portfolio betas are fixed and estimated via the full sample data. This assumes away the potential time-variations in these betas. Following Lewellen and Nagel (2006), I investigate the usefulness of US *MPU* risk in a setting with time-varying betas. At the end of each month t and for each currency portfolio, the time-series regression (2.3.1) is estimated by using the past five-year data from $t-59$ to t; then I run the following cross-sectional regression to estimate (via OLS) month-t prices of risk for the dollar factor and the risk of US MPU:

$$rx^i_{t+1} = \hat{\beta}^i_{DOL,t}\lambda_{DOL,t} + \hat{\beta}^i_{MPU,t}\lambda_{MPU,t} + \eta^i_{t+1}. \tag{2.5.1}$$

The left panel of Table 2.8 reports the mean and Newey-West standard errors of the rolling estimated MPU betas. Allowing for time-variations in fact leads to more significant high-minus-low beta spreads. The pattern of monotonically decreasing betas also does not change. Turning to the right panel, I find that the estimated prices for MPU risk are significant, with the t-statistic from the joint cross-section of carry and momentum reaching -3.4. Hence the main results are not affected by the time-varying betas.

Table 2.8. Robustness: Time-varying *MPU* betas

The table reports the statistics of rolling estimated MPU betas and risk prices from carry and momentum portfolios via the Fama-MacBeth regression. The regression is done via a 5-year rolling window estimation of Equation (2.3.1). Then the series of risk prices are obtained by running the cross-sectional regression (2.5.1), given the month-t MPU betas. Newey-West HAC standard errors are in parentheses with the optimal lag selection following Andrews (1991). The sample period is from January 1985 to August 2017.

	Statistics of MPU betas			Risk prices		
	Carry	Mom		Carry	Mom	Carry+Mom
L	0.15	0.18	λ_{DOL}	0.07	0.07	0.07
	(0.06)	(0.05)		(0.12)	(0.22)	(0.11)
2	0.07	0.10	λ_{MPU}	-0.59	-0.54	-0.62
	(0.02)	(0.04)		(0.22)	(0.28)	(0.18)
3	-0.02	-0.03				
	(0.04)	(0.05)				
4	-0.02	-0.05				
	(0.06)	(0.02)				
5	-0.17	-0.19				
	(0.09)	(0.07)				
HML	-0.32	-0.37				
	(0.14)	(0.10)				

2.5.3 G10 carry and currency-level asset pricing

I evaluate whether the newly documented return-beta relation exists among some well-known high or low interest rate currencies, such as the Australian Dollar (AUD) or Japanese Yen (JPY). Panel A of Table 2.9 reports the excess returns and *MPU* betas after sorting G10 currencies on their forward discounts. Interestingly, the return-beta relation found from portfolio-level analysis also translates to G10 currencies. High interest rate currencies such as AUD and GBP own negative *MPU* betas, while low interest rate currency JPY possess the highest *MPU* beta.

On the other hand, as widely discussed in e.g., Ang et al. (2017), forming portfolios for asset pricing test may destroy the information due to the shrinkage of cross-sectional beta dispersions. I thus study the pricing power of *MPU* risk at the country-level carry and momentum trades. First, the conditional currency excess return for currency i is defined as

$$crx_{t+1}^{i} = c_t^i rx_{t+1}^{i}, \tag{2.5.2}$$

where I consider two ways of incorporating the conditional information:

$$c_{1,t}^{i} = \begin{cases} sign(f_t^i - s_t^i), \\ sign(rx_t^i). \end{cases} \qquad c_{2,t}^{i} = \begin{cases} sign(f_t^i - s_t^i - \mathrm{med}(f_t - s_t)), \\ sign(rx_t^i - \mathrm{med}(rx_t)). \end{cases} \tag{2.5.3}$$

The first specification of sign functions follows Burnside et al. (2011) and Filippou et al. (2017), and the second type is as in Della Corte and Krecetovs (2017), which represents the sign of deviations from the cross-sectional median. These conditional returns are from the managed long-short strategies on individual currencies based on their carry or momentum signals. Since the panel of currency-level data is unbalanced, I follow Della Corte and Krecetovs (2017) by using the Fama-MacBeth regression to estimate risk prices. Panel B of Table 2.9 displays the results, where Newey-West t-statistics are based on the estimated series of risk prices, adjusted for the EIV problem of betas following Shanken (1992). The outcomes point to the negative and significant pricing of US *MPU* risk also at the currency-level.

Table 2.9. Robustness: Currency-level asset pricing

The table reports the results of currency-level asset pricing. Panel A reports the forward discounts, excess returns and *MPU* betas of G10 currencies (excl. USD). Panel B reports the estimated risk prices from the Fama-MacBeth regression by using the conditional currency excess returns of individual currencies. $C1$ is based on the conditional excess return that is defined as the raw excess return multiplied by the sign function of lagged interest rate differential or realized excess return, and $C2$ uses the sign function of the deviation from the cross-sectional median of lagged interest rate differential or realized excess return (detailed in Equation (2.5.3)). The Newey-West HAC standard errors are in parentheses with the optimal lag selection following Andrews (1991), and adjusted for the EIV problem of betas following Shanken (1992). The sample period is from January 1985 to August 2017.

	Panel A: G10 currency		
	Forward discount	Excess return	*MPU* beta
CHF	-1.92	0.02	0.02
JPY	-1.25	0.14	0.17
DEM/EUR	-0.35	0.14	0.08
CAD	0.63	0.08	0.03
SEK	1.18	0.15	-0.04
GBP	1.45	0.18	-0.28
NOK	1.65	0.21	-0.11
NZD	2.55	0.25	-0.05
AUD	3.44	0.45	-0.15

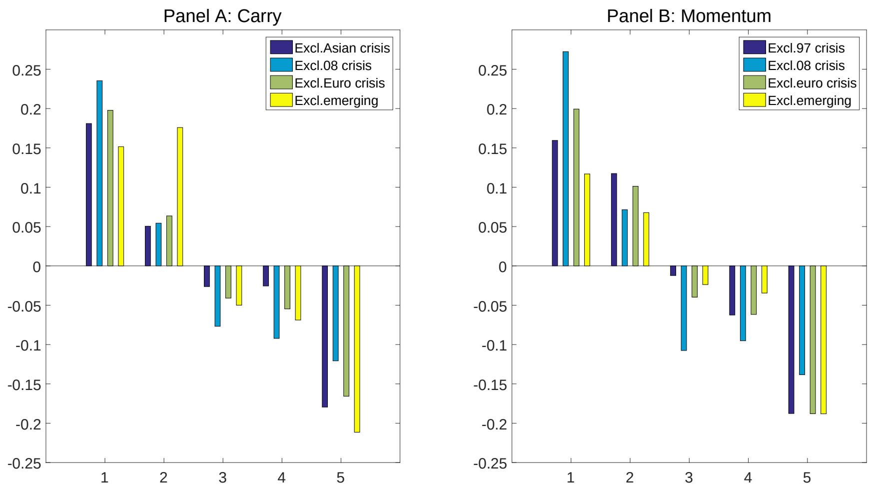
	Panel B: Conditional currency returns			
	$C1$		$C2$	
	λ_{DOL}	λ_{MPU}	λ_{DOL}	λ_{MPU}
Carry	3.71	-0.56	4.08	-0.47
(NW)	(1.36)	(0.22)	(1.69)	(0.21)
MOM	-5.00	-1.22	-4.18	-0.43
(NW)	(6.58)	(0.48)	(9.95)	(0.17)
Carry+MOM	2.93	-0.73	3.30	-0.32
(NW)	(1.43)	(0.19)	(1.72)	(0.10)

2.5.4 Subsample analysis and base currency

In this subsection, I assess the performance under a variety of subsamples over time and countries. I first exclude the periods of extreme market events that may be important to the FX market such as the 1997 Asian financial crisis, 2008 global financial crisis, as well as the Euro-debt crisis.[18] I also work over a subsample consisting of 21 developed countries, where the classification can be found in the Data Appendix. The estimated risk prices under these subsamples are in Panel A of Table 2.10. The pricing ability of *MPU* risk remains hardly affected and sometimes even stronger after removing the crisis periods. Figure 2.6 further plots the estimated *MPU* betas under these subsamples for carry and momentum portfolios.

Figure 2.6. ***MPU*** **betas under subsamples**

The figure plots the sensitivities of carry and momentum portfolio returns to the US *MPU* risk, estimated from Equation (2.3.1) by using data from different subsamples. The overall sample period is from January 1985 to August 2017.



I then study whether the main findings depend on the choice of base currency for the trade since up to now all results are from the perspective of a US investor, so that USD is the base currency. The theory suggests that the base currency is irrelevant because the exchange rate is determined by the financial intermediary instead of the households in any specific country. Panel B of Table 2.10 reports the results where the base currency switches to GBP, CAD, JPY and CHF respectively. Note that I take into account their bid-ask spreads against the USD when computing portfolio returns under these base currencies, since many currency pairs do not exist in the markets. The obtained risk price estimates are all negative and significant, with large cross-sectional R^2. The performance is unaffected by the choice of base currency.

[18] To avoid specific dating of these crisis periods, I simply remove the data from Jan 1997 to Dec 1998, from Jan 2007 to Dec 2009, and from Jan 2011 to Dec 2012 respectively.

Table 2.10. Robustness: Subsample and different base currencies

The table reports the results of asset pricing test under different subsamples (Panel A) or base currencies for the carry and momentum trade (Panel B). Switch of the base currency is established by taking into account the incurred bid-ask spreads when changing from USD to alternative base currency. The test is done via Fama-MacBeth regression, where I report the estimated risk prices, cross-sectional OLS R^2, the heteroskedastic and autocorrelation consistent (HAC) standard errors based on Newey and West (1987) with optimal lag selection following Andrews (1991) (NW), and the Shanken-adjusted standard errors of Shanken (1992) (Sh). The *p*-values of χ^2-test on the null hypothesis that the pricing errors are jointly zero are also reported. The sample period is from January 1985 to August 2017.

	λ_{DOL}	λ_{MPU}	R^2	χ^2_{NW}	χ^2_{Sh}
Panel A: Subsample analysis					
Excl. periods of Asian financial crisis	0.18	-1.56	0.97	[0.08]	[0.84]
(NW)	(0.11)	(0.34)			
(Sh)	(0.11)	(0.61)			
Excl. periods of 08 global financial crisis	0.14	-1.16	0.89	[0.02]	[0.51]
(NW)	(0.11)	(0.30)			
(Sh)	(0.11)	(0.47)			
Excl. periods of Euro-debt crisis	0.14	-1.50	0.98	[0.09]	[0.83]
(NW)	(0.11)	(0.33)			
(Sh)	(0.11)	(0.59)			
Excl. emerging countries	0.13	-0.76	0.90	[0.70]	[0.90]
(NW)	(0.11)	(0.25)			
(Sh)	(0.11)	(0.31)			
Panel B: Base currency of trade					
GBP	-0.08	-1.22	0.93	[0.00]	[0.19]
(NW)	(0.11)	(0.28)			
(Sh)	(0.11)	(0.44)			
CAD	0.01	-1.29	0.93	[0.00]	[0.32]
(NW)	(0.11)	(0.32)			
(Sh)	(0.11)	(0.52)			
JPY	0.09	-1.12	0.84	[0.00]	[0.20]
(NW)	(0.15)	(0.32)			
(Sh)	(0.15)	(0.48)			
CHF	-0.04	-1.30	0.80	[0.00]	[0.26]
(NW)	(0.11)	(0.33)			
(Sh)	(0.11)	(0.54)			

2.5.5 Additional robustness exercises

In the Internet Appendix, I report more results covering other aspects of robustness concern. First, I evaluate the asset pricing performance on the momentum portfolios formed over different window sizes, or formed by sorting on realized changes in log spot rates instead of excess returns. The latter exercise is an important check since Menkhoff et al. (2012b) show that there is a carry component within the momentum portfolios when sorting on excess instead of simple returns. Table A.1 and A.2 show that although the performance is slightly weaker for one-month momentum, with the joint cross-sectional R^2 now reduces to 86%, the main conclusions are largely unchanged: the high-minus-low beta spreads are significant and the *MPU* risk carries negative prices of risk.

Second, I check whether the pricing of *MPU* risk in carry trade portfolios alone overlaps with other uncertainties. To this end, I run a horse race with the set of uncertainty shocks listed in Table 2.1. For each uncertainty shock, I first report its pricing performance on five carry trade portfolios, then I add u_t^{MPU} as the control and the results are in Table A.3. Many uncertainties can price the carry trade portfolios, and the risk prices are also highly significant, following the findings in e.g., Menkhoff et al. (2012a) and Berg and Mark (2017). Nevertheless, after adding the *MPU* shocks, the magnitudes of risk prices decline a lot, and many of them even switch to the positive sign. On the other hand, the prices for the *MPU* risk are robustly negative. The improvement in the cross-sectional R^2 also points to the unique information in the US *MPU* risk even when pricing the carry portfolios.

Third, since the currency momentum may be tightly linked to the limits to arbitrage (see e.g., Menkhoff et al., 2012b), I test whether the role of *MPU* risk may be different for currencies with different limits to arbitrage. Following Filippou et al. (2017), at each month and for each currency, I compute the idiosyncratic volatility (idvol) and skewness (idskew) that serve as two measures for the limits to arbitrage.[19] Then I run double sort by first forming two groups of currencies

[19]The computation method follows Filippou et al. (2017) and is in the Internet Appendix.

based on their idiosyncratic volatility or skewness, and within each group, I form three momentum portfolios. Table A.4 and A.5 report the *MPU* betas of these portfolios and the results of asset pricing test. Whereas the profitability of FX momentum is generally higher among the currencies with stronger limits to arbitrage, the high-minus-low spreads in *MPU* betas are significant across these two groups of momentum portfolios. Also, compared with the baseline asset pricing results, the magnitudes of most of the cross-sectional R^2 are still large. Therefore, the main empirical findings in this paper are unlikely driven by limits to arbitrage.

2.6 Conclusion

This paper documents the importance of the risk of US monetary policy uncertainty on explaining the returns to FX carry and momentum trade. Its theoretical role is discussed in an exchange rate model featuring the financial intermediary with limited risk-bearing capacity, in the spirit of Gabaix and Maggiori (2015). The financial intermediary accommodates imbalanced asset flows between the US and foreign countries, and absorbs the resulting excess supply of USD or foreign currencies. I show that the intermediary optimally chooses to hold the top carry or momentum currencies, and short-sells the bottom carry or momentum currencies. The long-short behavior hence generates different responses to the US *MPU* shocks: higher *MPU* triggers position unwinding at both long and short side, leading to higher (lower) returns for top (bottom) carry or momentum currencies.

Empirically by using the US Monetary Policy Uncertainty (*MPU*) index of Baker et al. (2016), I show that the return sensitivities of currency carry and momentum portfolios to the US *MPU* shocks are monotonically decreasing from the bottom to the top, in line with the theory. The high-minus-low beta spreads are negative and statistically significant. These risk exposures explain 98% of the cross-sectional variations in mean returns of carry and momentum portfolios respectively. My results are similar if instead using other proxies of the US *MPU*, such as the realized variance of 10-year US Treasury bond yields. The explanatory power remains significant under a variety of settings and robustness checks. I then provide direct evidence to show that the US *MPU* risk significantly affects the intermediary constraints. By relating the financial frictions to the data on cross-border equity transactions channeled by the intermediary sector, I show that higher *MPU* predicts lower risk-taking activity of the financial intermediary. The predictive power is robust after controlling for the demand shock to the equity investor. In line with the view of intermediary asset pricing, the *MPU* risk is also priced in other asset classes including bonds, stocks, and options.

Chapter 3 Inflation Risk, Ambiguity, and the Cross-Section of Stock Returns

3.1 Introduction

Is inflation risk priced in the stock market? Intuitively, the inflation provides critical information on the future economic prospect (Fama, 1981) and hence will drive the time-varying investment opportunity set. According to the Intertemporal CAPM of Merton (1973), it should be priced in the stock market. Nevertheless, the stable relation between the inflation and the aggregate stock return remains hard to establish empirically (see e.g. Fama and Schwert, 1977; Fama, 1981; Bekaert and Engstrom, 2010, among many others). This poses significant challenge on assessing the inflation risk premium in the stock market. On the other hand, there is rising attention on how inflation is priced in the cross-section of stock returns. The large number of individual stocks and their heterogeneous inflation exposures are attractive for estimating the inflation risk premium, compared with a single aggregate stock index. However, the conclusions from this line of research are equally controversial. For example, Ang et al. (2012) find that the unconditional cross-section of inflation risk premium is small and insignificant. A recent paper by Boons et al. (2017) further documents strong time-variations in the inflation risk premium among individual stocks.

This paper uncovers a new driving force for the cross-sectional inflation risk premium (*CSIP*). I deviate from the rational expectation hypothesis by allowing the investor to distrust her model of inflation. The agent has a set of alternative models in her mind and she makes the optimal portfolio choice by showing aversion to such model uncertainty, or the so-called *ambiguity*. To provide economic intuition on how those ingredients work, I first build a consumption-based asset pricing model with ambiguity averse investor and inflation non-neutrality. The model implies that the equilibrium *CSIP* contains two components, which are compensations for fluctuating inflation and inflation ambiguity. The second part gives rise to a new source of inflation premium in the cross-section of stocks, which has not been documented by the prior literature.

The relevance of the ambiguity component stems from the endogenous link of two types of betas for the individual stock, that is, the exposures to inflation (inflation beta) and to inflation ambiguity (ambiguity beta). Sorting on inflation betas would be accompanied with either ascending or descending sort on ambiguity betas, depending on the aggregate economic states. Intuitively, since the ambiguity shock works as a *perceived* inflation shock for an ambiguity-averse agent, stock return's different response to changes in inflation would lead to the different response to changes in inflation ambiguity. Furthermore, their interaction is strongly affected by the exogenous co-movement of inflation and its ambiguity, i.e., the *nominal-ambiguity correlation* (*NAC*). At first glance, this is not surprising since if shocks to inflation and ambiguity co-move, the two betas would be related to some extent. However, I show that in the model, such a correlation will in fact overlap with the endogenous channel because the investor will take the correlated shocks into account when pricing those two risk factors. The nexus of endogenous and exogenous channels generates rich dynamics of the relation between two types of betas. For instance, I find that even though the endogenous channel suggests that stocks with high inflation betas also have high ambiguity betas, this relation could be destroyed if one further considers the exogenous channel and the magnitude of the ambiguity premium.

The theoretical predictions explain a variety of anomalies related to the inflation risk among individual stocks, such as the insignificant unconditional inflation risk premium (Ang et al., 2012), the occasional sign reversals (Boons et al., 2017), and the tight link between the inflation risk premium and the inflation forecast dispersion (Li, 2016). Moreover, I document new testable implications from the model. Following the literature (see e.g. Drechsler, 2013; Ulrich, 2013; Zhao, 2017) by using the forecast dispersion as the empirical proxy for the level of ambiguity, I find that the inflation beta and the ambiguity beta are indeed linked in a way consistent with the model prediction. Meanwhile, the nominal-ambiguity correlation, whose sign is the key switch for the interaction of inflation risk premium and ambiguity premium, strongly drives the *CSIP* both in- and out-of-sample. Positive *NAC* at the current quarter predicts in the following quarter a loss of *quarterly* return of -4.88% (-2.87%) for a zero-investment high-minus-low value-weighted (equal-weighted) portfolio, obtained by sorting on all individual stocks based on their exposures to inflation risk. Such an effect is economically large and statistically significant, and is robust under a variety of settings. The reason that positive *NAC* lowers the *CSIP* is because stocks with high inflation betas also have high ambiguity betas. Those stocks are then attractive for the ambiguity-averse investor since their returns are favorable when the ambiguity is high, and hence should command lower ambiguity premium. This mechanism translates to substantially lower *CSIP* observed in the data.

In addition to the entire universe of individual stocks, sorting out how inflation risk is priced in different industries is also a long-standing question among both the academia and the market practitioners (see e.g. Boudoukh et al., 1994; Lu, 2008; Ang et al., 2012). My model predicts that the ambiguity premium should also present at the industry-level. Empirically, I find that all industry-level inflation risk premia lower substantially when *NAC* becomes positive. For instance, the quarterly value-weighted inflation risk premia in the nondurable and durable sector decrease by -3.14% and -4.91% respectively when *NAC* changes from negative to positive. In fact, not only the magnitudes lower, the signs of the inflation risk premia also flip for most of the industries in a way consistent with the theoretical predictions.

Motivated by the strong predictive power of *NAC*, I propose a new and simple market-timing strategy for speculating on the inflation risk cross-sectionally. The strategy buys the portfolio with the lowest inflation beta and short-sells that with the highest inflation beta, when the current *NAC* is positive, and vice versa. The performance of the strategy directly sheds light on the economic benefit of the ambiguity channel. While the unconditional strategy implementing the usual wisdom that inflation commands negative risk price (Piazzesi et al., 2006) generates little profitability, I find that this simple conditional strategy based on the sign of *NAC* yields an annualized average excess return of 9.58% and 5.77%, with the annualized Sharpe ratio of 0.59 and 0.51 for value- and equal-weighted portfolios respectively. Both returns are highly significant and cannot be explained by the CAPM, Fama-French three- or five-factor models.

We note that the ambiguity premium stands in contrast with the existing resolutions for understanding the inflation risk and returns in the cross-section. In a recent paper, Boons et al. (2017) argue that the time-varying relation between inflation and future consumption growth, i.e., the nominal-real covariance (*NRC*) should determine the cross-sectional inflation risk premium . My model extends their framework by introducing the new component of ambiguity premium. Theoretically, the time-varying *NRC* and *NAC* are complementary forces. Nevertheless in the data, I find that the variations in *NAC* are more important determinants of *CSIP*. In particular, while the *NRC* can explain the *CSIP* computed from the value-weighted portfolios, it weakly captures other proxies of *CSIP*. Yet the explanatory power of *NAC* is more stable across horizons and measures of inflation risk premium. On the other hand, the ambiguity channel is directly linked to the behavioral-based explanation. Li (2016) empirically shows that the investor's disagreement over inflation will weaken the usual inflation risk-return relation at the cross-section, due to the channel of "speculative beta" proposed by Hong and Sraer (2016). While the mispricing of stocks with low inflation betas are essential for their story, this paper provides the ambiguity-based explanation where asset prices fully reflect the agent's belief. Importantly, my theory implies that the *NAC* should be the key predictor instead of the macro disagreement level in their papers.

I provide a battery of robustness checks to corroborate the main empirical finding. First, I introduce alternative ways of estimating the nominal-ambiguity correlation, which is a crucial check for the reliability of results. I find that while different estimates do vary in terms of their predictive power for the cross-sectional inflation risk premium, in most scenarios the effect is significant and in line with the benchmark results. Second, I control for more risk factors when estimating the inflation betas. I also control for other variables that may predict the cross-sectional inflation risk premium as discussed in Boons et al. (2017) and Li (2016), or surveyed by Welch and Goyal (2007) when testing the usefulness of *NAC*. The results are still significant under these settings. As a final set of robustness checks, I adopt other measures of inflation risk such as the factor-mimicking portfolio or the raw inflation series. The results though are somewhat noisier when using the factor-mimicking portfolio returns, the general pattern of predictive effect is robust, and using original inflation series as in Bekaert and Wang (2010) still yields the significant results.

Related literature This paper contributes to the long-standing yet still growing literature on how inflation risk is priced in the stock market (see e.g. Fama and Schwert, 1977; Boudoukh and Richardson, 1993; Bekaert and Wang, 2010; Bekaert and Engstrom, 2010; Eraker et al., 2016; Campbell et al., 2017). Despite stocks being commonly treated as the real assets whose real returns should not be affected by inflation (Fisher, 1930), the empirically negative relation between inflation and real stock returns has puzzled the financial economist since the seminal paper of Fama and Schwert (1977). While most of the previous studies seek to understand the pricing of inflation risk in the aggregate stock market, this paper joins in recent literature by investigating the role of inflation in the cross-section of stock returns. Ang et al. (2012) provide significant in-sample yet insignificant out-of-sample evidence on the negative price of inflation risk among individual stocks. Li (2016) attributes the insignificant pricing of inflation risk to the channel of speculative betas as in Hong and Sraer (2016), which is based on the mispricing instead of the ambiguity premium. Boons et al. (2017) build the analysis upon the conditional ICAPM model of Merton (1973) and Maio and Santa-Clara (2012) to show that the cross-sectional inflation risk premium is subject to strong time-variations, which is driven by the time-varying predictive relation of inflation on future consumption growth. My paper differs from theirs by highlighting the role of ambiguity premium and how its effect depends on the aggregate co-movement between inflation and ambiguity. Both results are novel in the context of the cross-section of stock returns, and are quantitatively important for understanding the inflation risk premium.

This paper is also related to the emerging literature studying the impact of ambiguity on asset prices. The extant focus is mainly on explaining the empirical facts at the aggregate-level markets such as the stock, bond and the derivative markets. Examples include Anderson et al. (2009), Hansen and Sargent (2010), Ju and Miao (2012), Drechsler (2013), Ulrich (2013), Zhao (2017) and in particular, see a review by Epstein and Schneider (2010). There is nevertheless increasing interest on studying the price of ambiguity in the cross-section of stocks (see e.g. Viale et al., 2014; Thimme and Völkert, 2015; Bali et al., 2016). My paper shows that the pricing of inflation risk and of its ambiguity at the stock-level is closely linked. Specifically, I establish the theoretical and empirical connection between the stock's inflation risk and ambiguity exposures, and focus more on how ambiguity premium affects the pricing of inflation risk.

Last but not least, my paper is connected to a strand of macroeconomic literature on the economic consequence of the correlation between inflation and inflation ambiguity (or inflation uncertainty). Such relation is important for evaluating the potential outcomes of monetary policy, see e.g. the theoretical discussions on its origin in Ball (1992), Mankiw and Reis (2002) and the empirical investigations in Mankiw et al. (2003), Capistrán and Timmermann (2009), Rich and Tracy (2010). Instead of exploring the cause of the co-movement, I focus on its implications on the pricing of inflation risk in the stock market, which to the best of my knowledge has not been done by the previous literature. I find that both the sign and the time-variations of the correlation, i.e., the *NAC*, can strongly explain the dynamics of the cross-sectional inflation risk premium.

3.2 Model

In this section I build a consumption-based asset pricing model with real effect of inflation and ambiguity averse investors. The model allows for tractable solutions for a variety of important quantities, and highlights how different ingredients determine the cross-sectional inflation risk premium, in particular the role of ambiguity premium.

3.2.1 Economy dynamics and preference

I start from specifying the state dynamics in the economy. First, the consumption growth follows

$$d\log C_t = (c_0 + \varepsilon \pi_t)dt + \sigma_c dW_t^c, \tag{3.2.1}$$

where π_t is the (demeaned) inflation and ε captures exogenously the inflation non-neutrality. Following Boons et al. (2017), it is named as the *nominal-real covariance* (*NRC*). The real effect of inflation is necessary to generate equilibrium pricing of inflation risk in the stock market. The (demeaned) inflation π_t follows

$$d\pi_t = -\kappa_\pi \pi_t dt + \sigma_\pi dW_t^p. \tag{3.2.2}$$

Suppose there are N stocks, with stock i's dividend process given by

$$d\log D_t^i = (d_0 + \varepsilon_i \pi_t)dt + \sigma_d dW_{it}^d, \quad i = 1, 2, \ldots N, \tag{3.2.3}$$

where for simplicity, I assume identical unconditional mean of dividend growth and volatility. Hence the specification indicates that those assets only differ in terms of their sensitivities to inflation (ε_i), and is in line with the usual empirical framework of forming cross-sectional portfolios based on the inflation risk exposures (see e.g. Ang et al., 2012). Also, the Brownian motions driving the economy are mutually independent.

The representative agent has the stochastic differential utility of Duffie and Epstein (1992), which can be treated as the continuous-time counterpart to the Epstein-Zin preference. However, I deviate from the rational expectation paradigm by allowing the agent to show aversion to the model uncertainty. The agent has in mind a reference model for *inflation*, which is the best model after various econometric steps including specification and estimation (see e.g. Kogan and Wang, 2003). Yet she distrusts it and worries that the true model may lie in a set of alternative models, which are hard to distinguish with the reference model based on the reasonable length of data. The agent solves for the optimal consumption-portfolio choice under the inflation model that yields the lowest lifetime utility, following Chen and Epstein (2002). In other words, the objective is described as

$$J = \min_{h} \max_{C} E_t^h[\int_t^\infty f(C_s, J_s) ds], \tag{3.2.4}$$

where the aggregator:

$$f(C,J) = \frac{\beta(1-\gamma)}{1-\frac{1}{\psi}} J[(\frac{C}{((1-\gamma)J)^{\frac{1}{1-\gamma}}})^{1-1/\psi} - 1]. \tag{3.2.5}$$

The choice variable h captures the process of optimizing under the alternative model for inflation, which will be made clear soon. In the aggregator, γ captures the relative risk-aversion and the ψ represents the elasticity of intertemporal substitution (EIS). In particular, when γ approaches $\frac{1}{\psi}$, the aggregator simplifies to that for the CRRA utility. To ease the notation, denote $\theta = \frac{1-\gamma}{1-1/\psi}$.

The inflation model uncertainty is represented by comparing all possible models through the likelihood ratio test, when the agent solves the optimal portfolio choice problem. Suppose the reference model generates the probability measure Q_t and an alternative model generates the measure Q_t^h. Denote Ξ_T as the likelihood ratio between those measures, then according to the specification of economy dynamics, one has:

$$\Xi_T = \exp(-\frac{1}{2}\int_0^T h_t^2 dt + \int_0^T h_t dW_t^p).$$

Clearly, different h_t yield different models and h_t corresponds to the choice variable in the problem (3.2.4). The optimal choice of h_t will then identify the worst-case model, which is obtained after applying the change of measure induced by the optimal h_t^* on (3.2.2):

$$d\pi_t = -\kappa_\pi \pi_t dt + \sigma_\pi h_t^* dt + \sigma_\pi dW_t^{h,p},$$

where $W_t^{h,p}$ is the Brownian motion under the worst-case model for inflation.

Similar to Chen and Epstein (2002) and Drechsler (2013), I assume that the expected change in the log-likelihood ratio is smaller than a stochastic upper bound $\rho\eta_t^2$, which essentially measures the size of the set of alternative models. Such a constraint is written as:

$$\frac{1}{2}h_t^2 \leq \rho\eta_t^2, \tag{3.2.6}$$

where ρ is the parameter governing the time-invariant investor's aversion towards model uncertainty, the process η_t captures the time-varying model uncertainty and is called the ambiguity process.[1] I assume that its dynamics follow

$$d\eta_t = \kappa_\eta(\bar{\eta} - \eta_t)dt + \sigma_\eta dW_t^\eta, \text{ with } E_t[dW_t^p dW_t^\eta] = \phi dt. \tag{3.2.7}$$

The key novelty of the specification is that I introduce the correlation between shocks to inflation and shocks to its ambiguity, as captured by ϕ. Such a specification is parsimonious and attractive since it incorporates more realistic co-movement

[1]The ambiguity process is exogenous to agent's portfolio choice problem. The exogeneity assumption can be understood following Hansen et al. (2006), that is, the ambiguity process is chosen ex-ante and the agent takes it as given when choosing the optimal model h_t.

as widely discussed in e.g. Mankiw et al. (2003), Capistrán and Timmermann (2009), Rich and Tracy (2010), to name a few. ϕ is labeled as the *nominal-ambiguity correlation (NAC)*. As it will be clear soon, the presence of *NAC* is crucial for the interaction of inflation risk and inflation ambiguity in the model.

3.2.2 Model solution

The equilibrium allocations and optimal choice for inflation model are obtained after solving the following constrained Hamilton-Jacobi-Bellman (HJB) equation (see also Epstein and Schneider, 2003; Drechsler, 2013):

$$\begin{aligned} 0 &= \min_h [f(C,J) + \mathscr{L}^h[dJ]], \\ s.t. \quad & \tfrac{1}{2}h_t^2 \leq \rho \eta_t^2, \end{aligned} \tag{3.2.8}$$

where $\mathscr{L}^h$ is the Dynkin operator under the probability measure of alternative model. I then conjecture that the value function takes the following form:

$$J(W,Y) = \frac{W^{1-\gamma}}{1-\gamma} \exp(A_0 + A_\pi \pi_t + A_\eta \eta_t), \tag{3.2.9}$$

where W is the agent's lifetime wealth, and the HJB equation can be written as

$$0 = \min_h \{\beta \theta J(K-1) + E_t^h [J_C dC + \tfrac{1}{2} J_{CC}(dCdC) \tag{3.2.10}$$

$$+ J_Y'(\mu(Y) + \sigma(Y)h) + \tfrac{1}{2} tr(J_{YY}\sigma(Y)\sigma(Y)')]\}, \tag{3.2.11}$$

$$s.t. \quad \tfrac{1}{2}h_t^2 \leq \rho \eta_t^2.$$

$Y_t = [\pi_t, \eta_t]'$ denotes the collection of state variables. The coefficients A_0, A_π and A_η can be solved out in closed-form from the above equation, after applying the log-linearizion similar to Chacko and Viceira (2005). The solution details are provided in the appendix. The equilibrium log wealth-consumption ratio from the model is

$$wc_t = \psi \log \beta + A_0 + A_\pi \pi_t + A_\eta \eta_t, \tag{3.2.12}$$

and the optimal model distortion takes the form

$$h_t = \begin{cases} \sqrt{2\rho}\eta_t, & \varepsilon < 0, \\ -\sqrt{2\rho}\eta_t, & \varepsilon > 0. \end{cases} \tag{3.2.13}$$

The factor loadings on π_t and η_t are given by

$$A_\pi = \frac{(1-\gamma)\varepsilon}{\psi\kappa_\pi + \psi e^{\bar{g}}}, \tag{3.2.14}$$

$$A_\eta = \begin{cases} \frac{\sigma_\pi\sqrt{2\rho}}{e^{\bar{g}}+\kappa_\eta}A_\pi, & \varepsilon < 0, \\ -\frac{\sigma_\pi\sqrt{2\rho}}{e^{\bar{g}}+\kappa_\eta}A_\pi, & \varepsilon > 0, \end{cases} \tag{3.2.15}$$

where $\bar{g}$ is the steady-state log consumption-wealth ratio.

Intuitively, when inflation has no real effect ($\varepsilon = 0$) or agent is risk-neutral ($\gamma = 1$), the optimal consumption and portfolio choice will not depend on the inflation, i.e. $A_\pi = 0$. Hence the inflation risk is not priced. In contrast, when the agent is risk-averse and the inflation has non-negligible real effect, since κ_π is positive for stationary inflation process, the denominator of (3.2.14) will always be positive. If inflation has negative impact on future growth ($\varepsilon < 0$), then $A_\pi > 0$ and the valuation ratio for the consumption claim will be lower when inflation is higher. This requires compensation for exposures to inflation risk. As the inflation shock becomes more persistent (κ_π is smaller), the negative effect on growth will be more persistent facing positive inflation innovation, the risk price for inflation then is higher under the recursive preference. The similar mechanism works for the case when $\varepsilon > 0$.

On the other hand, the model implies that the equilibrium wealth-consumption ratio also depends on the time-varying inflation ambiguity, as long as $A_\pi \neq 0$. First note from (3.2.13) that ε fully determines the sign of optimal model selection. When inflation predicts negatively the future growth, the expected utility of agent will be lower when the perceived inflation under the optimal inflation model is higher. Evidently, the correct *worst-case* model should correspond to the one that delivers the highest inflation forecast, and vice versa when $\varepsilon > 0$. Therefore the state-dependent choice for the worst-case model generates the state-dependent effect of ambiguity on the valuation ratio, as clearly shown in Equation (3.2.15). Interestingly, the sign of A_η is always positive regardless of the sign of ε. This is consistent with the specified preference that the agent dislikes the model uncertainty of inflation, no matter whether the inflation is good or bad signal for future consumption growth.

3.2.3 Equilibrium pricing kernel and asset pricing

I now formalize the asset pricing implications on the cross-section of stocks. Under the stochastic differential utility of Duffie and Epstein (1992), the pricing kernel is given by:

$$M_t = \exp[\int_0^t f_J ds] f_C. \tag{3.2.16}$$

Applying Itô's lemma and replacing in the equilibrium conditions, I obtain the dynamics for the equilibrium log pricing kernel:

$$d\log M_t = (\mu_0 + \mu_1^{'} Y)dt - \gamma d\ln C + \frac{\psi\gamma - 1}{\gamma - 1} A' dY, \tag{3.2.17}$$

where $\mu_0 = (\theta-1)e^{\bar{g}}(1-\bar{g}+\psi\ln\beta+(\psi-1)/(\gamma-1)A_0)-\beta\theta$, $\mu_1 = (\theta-1)e^{\bar{g}}(\psi-1)/(\gamma-1)A$. The real risk-free rate can be solved out as

$$r_{f,t} = -\frac{1}{dt}E_t^h[\frac{dM_t}{M_t}] = r_0 + r_\pi \pi_t + r_\eta \eta_t, \tag{3.2.18}$$

where the expressions for the coefficients are given in the appendix.

For the equilibrium prices of individual stocks, following (3.2.12), I conjecture that the dividend-price ratio of stock i also takes the exponentially affine form:

$$\frac{D_t^i}{P_t^i} = \exp(A_0^i + A^{i'} Y_t). \tag{3.2.19}$$

After going through similar steps as in the previous subsection, one can obtain

$$A_\pi^i = \frac{\varepsilon/\psi - \varepsilon_i}{\kappa_\pi + e^{\bar{g}_d}}, \tag{3.2.20}$$

$$A^i_\eta = \begin{cases} \frac{\sigma_\pi\sqrt{2\rho}}{e^{\bar{g}d}+\kappa_\eta}A^i_\pi, & \varepsilon < 0, \\ -\frac{\sigma_\pi\sqrt{2\rho}}{e^{\bar{g}d}+\kappa_\eta}A^i_\pi, & \varepsilon > 0, \end{cases} \tag{3.2.21}$$

Obviously, the sensitivities of log dividend-price ratio to inflation shock and ambiguity shock are tied up for every individual stock. This endogenous connection is due to the fact that ambiguity shock mimics the level shock for the ambiguity averse investor. Also, the effect depends on the sign of ε, that is, whether the inflation is good or bad signal for future consumption growth.

For the interest of comparing with the data, one need to obtain the equilibrium risk premium for stock i under the *reference* measure. Since the Euler equation holds only under the worst-case measure, the adjustment term of switching from the worst-case to the reference measure need to be added.

$$E_t[\frac{1}{dt}\frac{dP^i_t}{P^i_t} + \frac{D^i_t}{P^i_t}] - r_{f,t} = \beta^i_\pi\lambda_\pi + \beta^i_\eta\lambda_\eta - sign(\varepsilon)\eta_t A^i_\pi\sigma_\pi\sqrt{2\rho}. \tag{3.2.22}$$

where the betas are given by

$$\beta^i_\pi = \frac{Cov_t(d\pi_t, d\log P^i_t)}{Var_t(d\pi_t)} = -A^i_\pi - \frac{\phi\sigma_\eta}{\sigma_\pi}A^i_\eta, \tag{3.2.23}$$

$$\beta^i_\eta = \frac{Cov_t(d\eta_t, d\log P^i_t)}{Var_t(d\eta_t)} = -A^i_\eta - \frac{\phi\sigma_\pi}{\sigma_\eta}A^i_\pi, \tag{3.2.24}$$

and the prices of risk are given by

$$\lambda_\pi = -\frac{\psi\gamma-1}{\gamma-1}A_\pi\sigma^2_\pi, \tag{3.2.25}$$

$$\lambda_\eta = -\frac{\psi\gamma-1}{\gamma-1}A_\eta\sigma^2_\eta. \tag{3.2.26}$$

From the equation, it is clear that under the worst-case measure, the risk premium is subject to a two-factor structure, and is constant. However, since the drift distortion is time-varying, the last term is induced by switching the measure. When inflation is good for aggregate economy, if stock i is negatively exposed to inflation shocks,

The two components in (3.2.22) represent the compensation for the fluctuating inflation and inflation ambiguity. The inflation beta (β^i_π) and the ambiguity beta (β^i_η)

capture respectively, the exposure of individual stocks to aggregate-level inflation and ambiguity changes. Unsurprisingly, these two types of betas depend on how the price-dividend ratio reacts to each of the shocks (A^i_π and A^i_η). An interesting observation is that after allowing for non-zero nominal-ambiguity correlation ϕ, the inflation (ambiguity) beta for stock i now contains a part related to the sensitivity to the ambiguity (inflation) shocks. Agent in equilibrium will take the contemporaneously correlated shocks into account and she therefore price the two risk factors jointly.

The usual measure of the cross-sectional inflation risk premium (*CSIP*) is the return spread of inflation beta sorted portfolios. In the model this is written as:

$$CSIP = (\beta^H_\pi - \beta^L_\pi)\lambda_\pi + (\beta^H_\eta - \beta^L_\eta)\lambda_\eta - sign(\varepsilon)\eta_t\sigma_\pi\sqrt{2\rho}(A^H_\pi - A^L_\pi), \quad (3.2.27)$$

where β^η_H (β^η_L) denotes the ambiguity beta for the portfolio with the highest (lowest) inflation beta.[2] Given the connection between two types of betas, the inflation ambiguity premium may amplify or counteract the pure inflation risk premium. The more detailed exploration on the mechanism can be summarized by the following proposition.

PROPOSITION 2. *Suppose the ambiguity-averse investor is risk-averse* ($\gamma > 1$), *and prefers early resolution of uncertainty* ($\gamma > \frac{1}{\psi}$).

(i) if $\varepsilon < 0$, $\phi > 0$, *then* $CSIP < 0$, *and* $\beta^\eta_H > \beta^\eta_L$;

(ii) if $\varepsilon > 0$, $\phi < 0$, *then* $CSIP > 0$, *and* $\beta^\eta_H < \beta^\eta_L$.

In particular, define $\bar{\phi} = \frac{e^{\bar{g}} + \kappa_\eta}{\sqrt{2\rho}\sigma_\eta}$,

(iii) if $\phi > \bar{\phi}$, *then* $CSIP < 0$, *and* $\beta^\eta_H > \beta^\eta_L$;

(iv) if $\phi < -\bar{\phi}$, *then* $CSIP > 0$, *and* $\beta^\eta_H < \beta^\eta_L$.

The idea behind the proposition is simple and visualized in Figure 3.1. As discussed before, two components will emerge when the investor requires compensa-

[2] By construction, $\beta^H_\pi > \beta^L_\pi$, but this is not necessarily true for ambiguity beta.

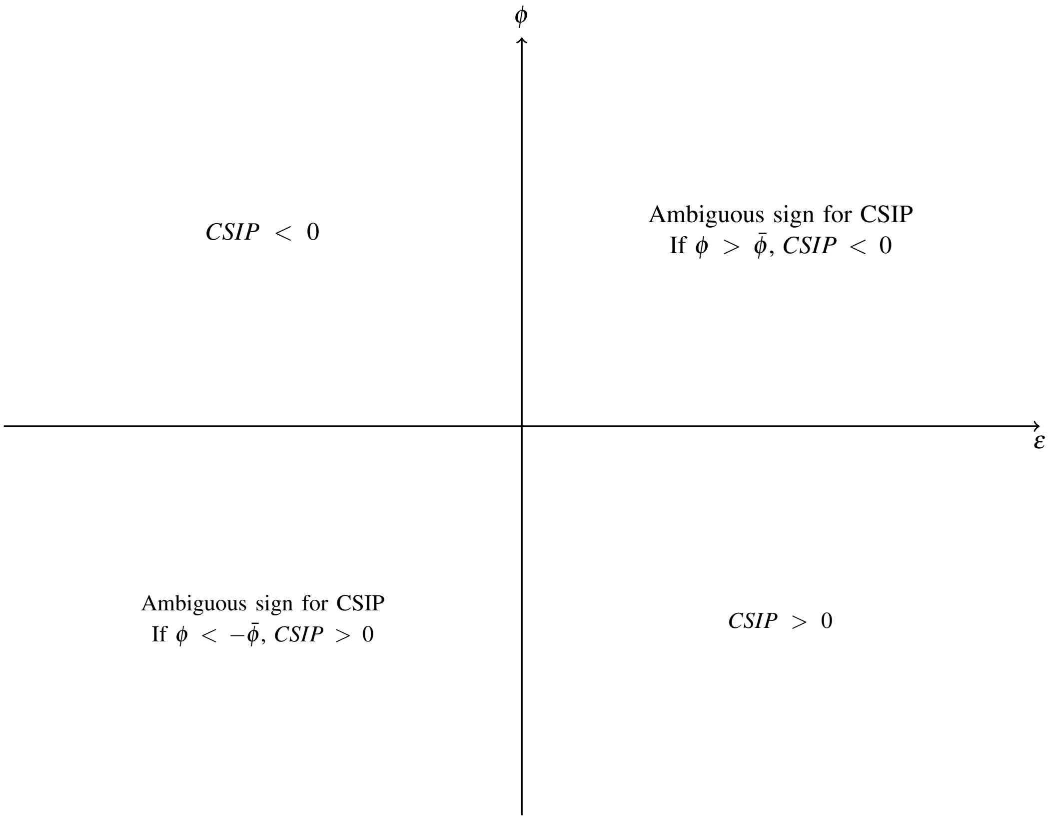
tion for taking on the inflation risk. More importantly, their "directions" change across different economic regimes. For example, when $\varepsilon > 0$, then inflation is good and the compensation for inflation risk is positive, i.e., stocks with high inflation betas have high risk premia because they perform poorly when inflation is lower. If further the *NAC* (ϕ) is positive, then stocks having high inflation betas also *tend* to have high ambiguity betas, especially when the ambiguity is strongly priced ($\bar{\tau}$ is large). However, high ambiguity beta stocks should command lower risk premium for an investor with ambiguity aversion. Under such scenario (depicted in the first quadrant of Figure 3.1), the ambiguity component counteracts the inflation risk premium and the *CSIP* takes the ambiguous sign. In particular, if one expects that the ambiguity premium is large, then from Equation (3.2.23), sorting on inflation betas may end up with a sort on the sensitivity to ambiguity shocks A^i_η. Under such a scenario, even though the theoretical sign based on the rationale of ICAPM is positive, the empirical *CSIP* ends up with negative sign due to the ambiguity hedging property of stocks with high inflation betas ($\beta^H_\eta > \beta^L_\eta$).

The picture becomes totally different when it goes to the second quadrant. Now since $\varepsilon < 0$, then the ICAPM-dictated risk price for inflation should be negative, that is, stocks with high inflation betas have lower returns. On the ambiguity side, since ϕ is positive, the ambiguity hedging property of those stocks still presents. Put differently, the compensation for inflation risk and inflation ambiguity aligns with each other. The resulting implication is such that the *CSIP* will always be negative, as well as for the spread in ambiguity beta, as plotted in Figure 3.1.

The economic intuition is similar for other two quadrants. Overall, the model predicts that when there is the sizable concern on the model uncertainty (high ρ), or highly persistent ambiguity shocks (low κ_η), or very volatile ambiguity shocks (high σ_η), then even though the channel of ICAPM is still alive, the ambiguity part will be the most important determinant. This is clear from (iii) and (iv).

Figure 3.1. Model implications

The figure plots the theoretical predictions on the interaction of inflation risk premium and inflation ambiguity premium, as well as two types of betas under different economic regimes. The horizontal axis (ε) represents the nominal-real covariance (NRC) of Boons et al. (2017), and the vertical axis (ϕ) represents the nominal-ambiguity correlation (NAC). The first to the fourth quadrant denotes respectively the regime of (i) $\varepsilon > 0$, $\phi > 0$; (ii) $\varepsilon < 0$, $\phi > 0$; (iii) $\varepsilon < 0$, $\phi < 0$; (iv) $\varepsilon > 0$, $\phi < 0$.



3.3 Empirical Results

In this section I provide extensive tests on the new theoretical predictions. I first describe the data and related econometric steps, then I report the main empirical results.

3.3.1 Data and methodology

Following Drechsler (2013) and Ulrich (2013), the level of inflation model uncertainty (ambiguity) is measured via the dispersion of professional forecasters in the next quarter's inflation rate. The dispersion is constructed as the difference between the 75th percentile and the 25th percentile of forecasters' projections, and is available from the Phildelphia Fed's Survey of Professional Forecasters (SPF). The quarterly data range from Q3 of 1981 to Q4 of 2017. The inflation is measured as the monthly changes of the log of the seasonally adjusted U.S. Consumer Price Index (CPI) for All Urban Consumers. Since my paper focuses on the interaction between inflation risk premium and ambiguity premium, I take its sample starting from July of 1981 to be consistent with the ambiguity data.

I collect monthly stock returns from the Center for Research in Security Prices (CRSP). The sample includes all common stocks with share code of 10 or 11 listed on NYSE, NASDAQ, and Amex. The returns on common risk factors and risk-free rates are from Kenneth French's website. To estimate the inflation beta, I first obtain the shocks to the monthly inflation (u_t^{π}) by running the regression:

$$\pi_t = \alpha_0 + \alpha_1 \pi_{t-1} + u_t^{\pi}. \tag{3.3.1}$$

The equation is estimated using an expanding window (with the initial window size of 60 months) and updated on the monthly basis. This is to avoid the look-ahead bias when estimating the shocks. Then the inflation beta for the stock i is estimated via a 5-year rolling window on the following equation:

$$r_{it}^{e} = \alpha_i + \beta_{im} MKT_t + \beta_{i\pi} u_t^{\pi} + \zeta_t, \tag{3.3.2}$$

where I control for the market factor when estimating the sensitivity of stock i's excess returns to inflation shocks.

As implied from the theory, the nominal-real covariance (*NRC*) and the nominal-ambiguity correlation (*NAC*) are important for understanding the inflation risk premium. To obtain their empirical proxies, I first follow Boons et al. (2017) by estimating the quarterly predictive regression of using current inflation to forecast future U.S. real consumption growth:

$$\Delta c_{t-h:t} = \alpha_t + NRC_t \pi_{t-h} + \xi_{t-h:t}, \tag{3.3.3}$$

where NRC_t (for horizon h) is treated as the quarter t's nominal-real covariance and the regression is estimated via a 20-quarter rolling window with data up to quarter t. The forecasting horizon h ranges from one-quarter to four-quarter. On the other hand, note that the nominal-ambiguity correlation (*NAC*) concerns the *contemporaneous* relation between shocks to inflation and shocks to ambiguity. To obtain the *NAC* for quarter t, I use the simple time-varying correlations between those two shocks, computed from a 5-year rolling window by only using data up to quarter t.

The upper plot of Figure 3.2 displays the estimated *NRC* under different choices for h. In line with the monthly-based estimates in Boons et al. (2017), the quarterly *NRC* is also negative for most of the time, suggesting that higher inflation predicts lower consumption growth in the future. Importantly, the inflation-growth nexus fluctuates in a similar fashion under different forecasting horizon. I hence follow Boons et al. (2017) by treating *NRC* estimated under $h = 4$ as the benchmark measure used later in the empirical test.[3] The *NAC* is plotted in the lower panel of

[3]The result for other horizons is quite similar and is available from the author upon request.

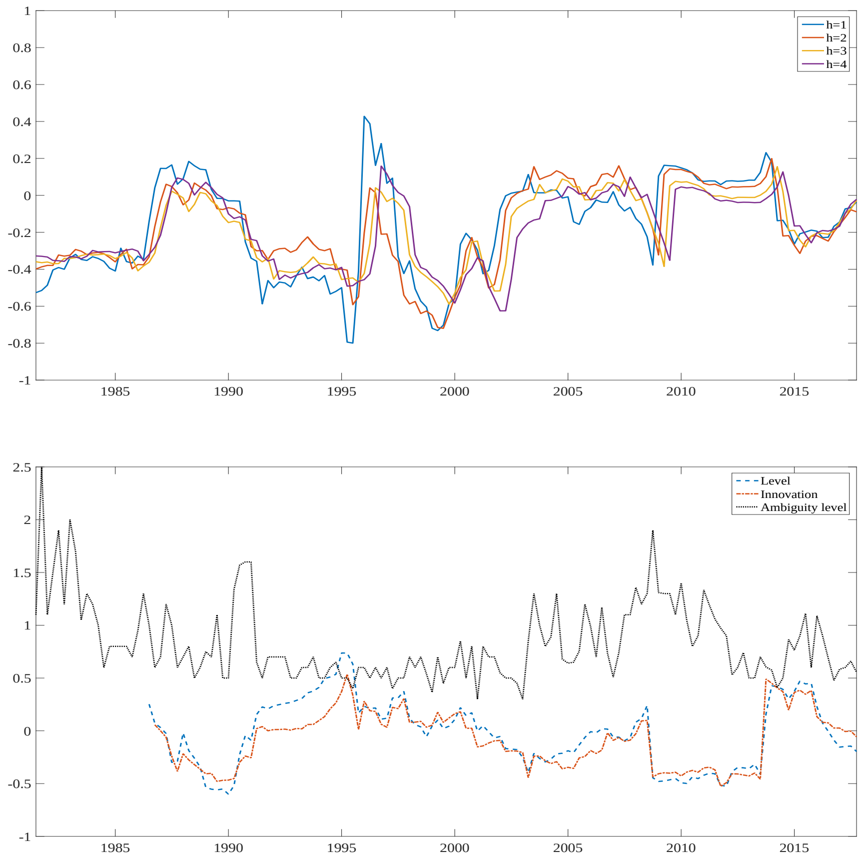
Figure 3.2 together with the ambiguity level, as well as the time-varying correlations computed from the *level* of inflation and ambiguity. Compared with *NRC*, the sign reversals of *NAC* are more dramatic. For example, while *NAC* changes from positive to negative from 1995 to 2010, it re-bounces to large and positive level during the post-crisis period, and this is true for correlations obtained either from levels or from shocks.

Figure 3.2. Nominal-ambiguity correlations and ambiguity level

The upper panel plots the nominal-real covariance (NRC) estimated using a rolling window of 20-quarter, under the forecasting horizons range from one-quarter to four-quarter:

$$\Delta c_{t-h:t} = \alpha_t + NRC_t \pi_{t-h} + \xi_{t-h:t},$$

where Δc_t is the consumption growth of nondurables and services, and π_t is the quarterly inflation computed as the log changes in quarterly CPI. The quarter-t estimates are based on the data up to quarter t. The lower panel plots the inflation ambiguity level, together with the 20-quarter rolling estimated time-varying correlations between (innovations in) inflation and (innovations in) ambiguity. Data sample ranges from Q3 of 1981 to Q4 of 2017.



3.3.2 Portfolios sorted on inflation betas

At the end of each month, all stocks are sorted based on their past inflation betas. Then each stock is attributed to one of the decile portfolios, where the portfolio 1 (10) contains stocks with the lowest (highest) inflation betas. I record the realized portfolio excess return in the following month for each portfolio, where the excess returns are computed using either equal-weighted (EW) or value-weighted (VW) scheme. All the portfolios are rebalanced monthly.

Table 3.1 reports the average annualized portfolio excess returns under both weighting schemes. Consistent with the prior findings in Ang et al. (2012), the cross-sectional inflation risk premium is negative yet insignificant.[4] The annualized return of -1.41% from the value-weighted portfolios though is of larger magnitude than that from the equal-weighted portfolios, it is still insignificant with a t-statistic of only -0.50.

One answer to this result is simply that the inflation is not priced in the stock market, which does not fit well with the usual economic intuition due to its central role in the policy making or economic growth at the macro-level, and that in the firm's long-term planning at the micro-level. A more promising resolution is that the insignificant unconditional results may mask substantial conditional movements or time-variations. That is, the inflation is conditionally priced despite the unconditionally insignificant result. This idea has been well pursued by Jagannathan and Wang (1996) and Lewellen and Nagel (2006) for the classical CAPM, though much less work has been carried out on understanding the pricing of macroeconomic risk.

Before turning to the conditional results, I discuss the post-formation inflation betas for the decile portfolios following Fama and French (1992). One should expect that sorting on pre-formation betas can generate ascending post-formation betas. This is an important justification on the method for beta estimation (and thus

[4]By adding specific control variables when estimating betas and forming portfolios, Boons et al. (2017) is able to find the significant *CSIP* for the value-weighted portfolios under a different sample period. My paper instead follows more closely the usual procedures of estimating betas and portfolio formation, and focuses on both the equal- and value-weighted portfolios.

the portfolio construction), and is also a necessary check on whether the inflation is a useless factor because it is not a traded factor (Kan and Zhang, 1999). For each portfolio, I obtain the post-formation inflation betas by estimating Equation (3.3.2) using the full-sample portfolio excess returns (by controlling for the market factor), the results are also tabulated in Table 3.1. Apparently, the post-formation inflation betas increase almost monotonically from the lowest decile to the highest decile, for both equal- and value-weighted portfolios. The high-minus-low inflation beta spreads are also positive and significant, with 3.24 (t-stat. 4.36) and 2.18 (t-stat 1.99) respectively. From the perspective of searching for good inflation hedges, while a majority of value-weighted portfolios turn out to be bad inflation hedgers (negative betas), the equal-weighted portfolios maintain unanimously good inflation hedging ability. This matches the empirical observation from Ang et al. (2012) that the best ex-post inflation hedgers are small stocks, which usually dominate the characteristics of equal-weighted portfolios.

Table 3.1. Decile portfolios sorted by inflation betas

This table reports the annualized average excess returns (in percentage) as well as the post-formation inflation betas of decile portfolios and the high-minus-low portfolio. At the end of each month, all stocks are sorted based on the inflation betas into 10 portfolios. The portfolios are rebalanced monthly and average excess returns are computed under either equal-weighted (EW) or value-weighted (VW) scheme. The post-formation inflation betas are obtained by estimating the following equation using the full-sample monthly returns of portfolio i:

$$r_{it}^{e} = \alpha_i + \beta_{im} MKT_t + \beta_{i\pi} u_t^{\pi} + \zeta_t,$$

where MKT_t is the market factor, and u_t^{π} is the inflation shock. The t-statistics are reported in the parentheses and based on the standard errors of Newey and West (1987) with optimal lag selection following Andrews (1991). The data from September 1976 to August 1981 are used for initial estimation of inflation betas. The sample for the portfolio returns starts from September 1981 to December 2017.

	EW		VW	
	Excess returns	Post-form. infl betas	Excess returns	Post-form. infl betas
L	11.17	1.34	8.07	-0.71
	(2.34)	(1.86)	(2.15)	(-1.63)
2	11.75	0.58	8.89	-0.07
	(3.03)	(1.06)	(2.90)	(-0.18)
3	11.96	0.38	8.08	-0.85
	(3.48)	(0.65)	(2.88)	(-2.68)
4	11.50	0.58	8.12	-0.01
	(3.45)	(1.17)	(2.79)	(-0.01)
5	11.46	0.51	9.59	-0.64
	(3.48)	(1.01)	(3.51)	(-2.73)
6	11.66	0.66	9.13	0.00
	(3.45)	(1.65)	(3.39)	(0.01)
7	11.65	1.13	8.57	-0.40
	(3.20)	(1.97)	(2.93)	(-0.96)
8	10.68	1.43	8.87	0.51
	(2.72)	(2.56)	(2.87)	(0.68)
9	11.09	2.72	9.19	0.85
	(2.46)	(3.85)	(2.45)	(1.19)
H	10.96	4.58	6.66	1.46
	(1.99)	(4.25)	(1.35)	(1.50)
HML	-0.21	3.24	-1.41	2.18
	(-0.10)	(4.36)	(-0.50)	(1.99)

3.3.3 Understanding the inflation risk premium and the ambiguity channel

As a first look on the ambiguity channel, I compute the empirical counterparts of various predictions as given in Figure 3.1. This is a straightforward and stringent test on the relevance of ambiguity premium. For the measures of *CSIP*, in addition to the high-minus-low return spreads of decile portfolios, I also consider the third measure from the stock-level returns (see e.g. Boons, 2016; Ang et al., 2017). Such a measure is attractive since the rich and heterogeneous information in the entire universe of individual stocks could provide more efficient estimates compared with the portfolio-level measures. More specifically, I follow Ang et al. (2017) by first running the regression (3.3.2) for each individual stock and by using the data up to month t (five-year rolling window). This step generates month-t estimate of inflation betas. Then I run the following cross-sectional regression (CSR) using all available stocks at month t:

$$r^{ei}_{t+1} = \hat{\beta}^i_{mkt,t}\lambda_{mkt,t} + \hat{\beta}^i_{\pi,t}\lambda_{\pi,t} + \varepsilon^i_{t+1}, \quad i = 1,2,\ldots N_t, \tag{3.3.4}$$

where $\hat{\beta}^i_{mkt,t}$ and $\hat{\beta}^i_{\pi,t}$ are the first-pass estimated market and inflation betas. The zero beta rate is imposed throughout all CSR. The stock-level inflation risk premium $\lambda_{\pi,t}$ can be interpreted as the return of a zero-cost investment portfolio with pre-formation inflation beta equal to one (Fama, 1976). Table 3.2 reports the statistics of three risk premium measures, as well as their correlations with several macroeconomic and financial variables.[5]

The inflation risk premia obtained using different methods are strongly correlated with each other, with the highest correlation reaches 0.80 between the stock-level risk premium and the return spread of equal-weighted portfolios. Nevertheless, the higher moments differ to some extent. For example, the *CSIP* estimated from VW

[5] In order to be quantitatively comparable with the two portfolio-level measures, I scale the estimated $\lambda_{\pi,t}$ first by the post-formation inflation beta of the portfolio inherent in the regression (3.3.4) and then by the post-formation inflation beta spread of value-weighted portfolios, which is 2.18.

portfolios are more volatile than that from EW or stock-level returns. Additionally, while the skewness of VW-based estimates is negative (-0.25), the stock-level *CSIP* shows positive skewness with 0.51, and the kurtosis of stock-level estimates almost doubles those from the portfolio-level risk premium. The descriptive statistics suggest that despite the strong co-movement, these measures have important heterogeneities which may capture different aspects of cross-sectional inflation risk premium. Meanwhile, the three measures show almost no correlations with a battery of variables characterizing the economy and financial market. The inflation, growth and recession dummy are not correlated with *CSIP*. This is also true for other variables that are well-known drivers for the stock market risk premium (Welch and Goyal, 2007). The evidence hence reveals the difficulty of sorting out the source of variations in the cross-sectional inflation risk premium.

With the estimated inflation risk premia, Figure 3.3 depicts the empirical results within each of the four quadrants corresponding to the theoretical implications in Figure 3.1. A striking observation is that the inflation risk is strongly priced in the cross-section of stocks *conditional* on the signs of ε and ϕ, in spite of the insignificant unconditional risk premium. For instance, the annualized inflation risk premium from the value-weighted portfolios reach -12.35% when $\varepsilon < 0$ and $\phi > 0$, yet it switches to 14.68% when $\varepsilon > 0$ and $\phi < 0$. Remarkably, while the inflation risk premia are negative for three measures when $\phi > 0$, they all switch to positive values when $\phi < 0$. This matches well the predictions from Proposition 2, under the case in which the ambiguity premium is large enough.

Another important check is on the link between the inflation betas and ambiguity betas. To this end, I estimate the quarter-t exposure of high-minus-low inflation beta sorted portfolio (value-weighted) to the ambiguity shock u_t^{η}:

$$r_t^{HML} = \alpha + \beta_m MKT_t + \gamma u_t^{\eta} + \varepsilon_t, \tag{3.3.5}$$

where u_t^{η} is obtained from applying the AR(1) model on the series of inflation ambiguity similar to (3.3.1). The regression is estimated by using the data from $t-20$

Table 3.2. Descriptive statistics of cross-sectional inflation risk premium

This table presents the summary statistics of three measures for the cross-sectional inflation risk premium (upper panel) and their correlations with the economic factors (lower panel). The three measures include the high-minus-low return spreads of value-weighted (VW) and equal-weighted (EW) inflation beta sorted decile portfolios, and the stock-level risk premium estimates (Stock) from the cross-sectional regression

$$r^{ei}_{t+1} = \hat{\beta}^{i}_{mkt,t}\lambda_{mkt,t} + \hat{\beta}^{i}_{\pi,t}\lambda_{\pi,t} + \varepsilon^{i}_{t+1}.$$

The stock-level estimates $\lambda_{\pi,t}$ are first scaled by the post-formation beta of the portfolio implied in the above regression, and then by the post-formation beta spreads of value-weighted portfolios. Inflation is the log changes of monthly CPI, and Growth is the consumption growth of nondurables and services. NBER dummy stands for the NBER recession dummy. MKT is the U.S. aggregate stock excess return. D/P is the log dividend-price ratio of S&P 500 index. Default spread is the difference between BAA and AAA-rated corporate bond yields, and Term spread is the difference between the long-term yield on government bonds and the Treasury-bill. VIX is the implied volatility on the S&P 500 index options. TED spread is the difference between the interest rates on interbank loans and T-bill rate. Data sample ranges from September 1981 to December 2017.

	VW	EW	Stock
Mean (%)	-1.41	-0.21	-0.24
Stdev (%)	16.47	11.45	8.88
Skew	-0.25	-0.09	0.51
Kurt	5.34	6.87	11.11
AR(1)	-0.01	0.04	0.15
		Correlation	
VW	1.00		
EW	0.69	1.00	
Stock	0.59	0.80	1.00
Inflation	0.08	0.09	0.06
Growth	0.01	-0.03	-0.10
NBER Dummy	-0.04	-0.02	-0.02
MKT	0.22	0.20	0.06
D/P	0.01	-0.03	-0.10
Default spread	-0.04	-0.02	-0.02
Term spread	-0.03	0.09	0.08
VIX	-0.09	-0.04	-0.02
TED spread	0.02	-0.01	-0.05

to t, that is, via a 20-quarter rolling window.[6] The average of estimated ambiguity betas conditional on the signs of ε and ϕ are also displayed in Figure 3.3. Consis-

[6]The monthly portfolio returns are compounded to obtain the quarterly returns.

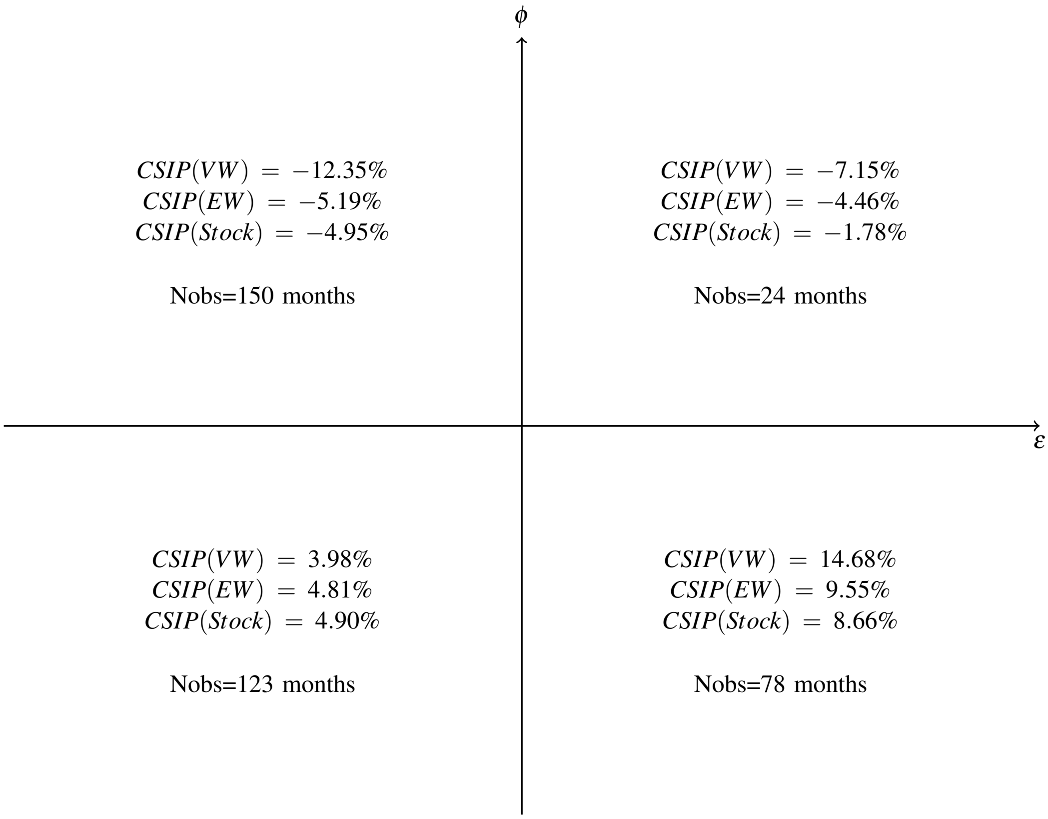
tent with the theory and the previous findings for the pattern of risk premium, high inflation beta stock is also better hedge to the inflation ambiguity shock when ϕ is positive, as shown by the ambiguity beta spread of 19.38 and 6.03. This translates to the counteracting and amplifying effect respectively in the first and the second quadrant, and vice versa when ϕ is negative.

Figure 3.3. Regime-dependent link of two betas and inflation risk premium

This figure displays the conditional average of inflation risk premium and the rolling estimated ambiguity betas from:

$$r_t^{HML} = \alpha + \beta_m MKT_t + \gamma u_t^{\eta} + \varepsilon_t,$$

where r_t^{HML} is the high-minus-low quarterly returns of the decile portfolios sorted by inflation betas (value weighted), obtained by compounding the within-quarter monthly returns. u_t^{η} is the quarterly shocks to the inflation ambiguity. The quarter-t ambiguity beta γ is estimated via a 20-quarter rolling window by using data up to quarter-t. The three annualized inflation risk premium measures are excess returns of high-minus-low equal-weighted (EW) and value-weighted (VW) portfolios, and the stock-level inflation risk premium, scaled by the post-formation inflation beta spread of value-weighted portfolios (Stock). The averages are computed over four regimes characterized by the signs of NRC (ε) and NAC (ϕ), where the average returns are based on the monthly data in the following quarter, and the average of ambiguity betas are based on the current quarter when conditioning information. Data sample ranges from October 1986 to December 2017.



3.3.4 Forecasting cross-sectional inflation risk premium

While the ambiguity channel is successful at generating salient features of qualitative facts, in this subsection I evaluate statistically the power of *NAC* in driving the cross-sectional inflation risk premium. I run the following predictive regression:

$$r^{CSIP}_{t+1:t+h} = a + b_{NAC}\mathbb{I}_{NAC_t>0} + \varepsilon_{t+1:t+h}, \tag{3.3.6}$$

where $r^{CSIP}_{t+1:t+h} \in \{VW, EW, Stock\}$ denotes one of the three measures for *CSIP*, and h is the forecasting horizon. Equation (3.3.6) aims to test the prediction that when NAC_t changes from negative to positive, the *CSIP* should move from positive to negative, i.e., b_{NAC} should be negative. Also, I choose the dummy indicating the sign of NAC_t instead of the raw *NAC* as the predictor to alleviate the impact of estimation error of *NAC*.[7] On the other hand, the inference of (3.3.6) is challenging due to the persistence of the dummy variable, with the AR(1) coefficient of 0.86 (see e.g. Stambaugh, 1999). I thus evaluate the predictive power of the dummy $\mathbb{I}_{NAC_t>0}$ over alternative forecasting horizons, and employ both the standard errors of Newey and West (1987) and the recently proposed IVX-Wald test following Kostakis et al. (2014) to achieve robust inference for the predictive coefficients b_{NAC}.

The regression results are displayed in Table 4.5. In line with Figure 3.1, the sign of *NAC* indeed predicts the future cross-sectional inflation risk premium with the theoretical sign, for all horizons and proxies for *CSIP*. The slope coefficient b_{NAC} is economically large and statistically significant. For instance, at the one-quarter horizon, positive *NAC* predicts a quarterly loss of 4.88% (2.87%) for the return of high-minus-low value- (equal-) weighted portfolios, and the effect is significant under the usual Newey-West t-statistics and the IVX-Wald test of Kostakis et al. (2014). The statistical significances of other proxies and horizons are very similar or even stronger. The in-sample R^2_{IS} indicates that simple sign switches in *NAC* can explain 5.90% to 7.44% variations in the next quarter's inflation risk premium. And

[7] The results using the raw *NAC* are similar.

the explanatory power increases to around 10% for half-year horizon or beyond.

As is widely discussed in the literature of aggregate stock return predictability (see e.g. Welch and Goyal, 2007; Rapach et al., 2016a), the full-sample result though is more powerful at testing the predictive ability statistically, rising attention has been switched to simultaneously evaluate the out-of-sample (OOS) performance. In addition to being an important model diagnostic for the usefulness of explanatory variable, it is also a relevant measure for the investor's real-time benefit (Campbell and Thompson, 2007). Hence I follow the literature by calculating the out-of-sample R^2_{OOS} as:

$$R^2_{OOS} = 1 - \frac{\sum_{t=N}^{T-h}(r_{t+h} - \hat{r}_{t+h})^2}{\sum_{t=N}^{T-h}(r_{t+h} - \bar{r}_{t+h})^2}, \tag{3.3.7}$$

where $\hat{r}_{t+h}$ is the predicted $h-$period ahead return from the model (3.3.6), and $\bar{r}_{t+h}$ is the historical average of realized $CSIP$, both quantities are estimated with data up to time t. Therefore, R^2_{OOS} essentially compares the real-time forecasting performance of candidate predictor with the historical average benchmark for the returns.

The R^2_{OOS} are reported in the last column of Table 3.3, where I also attach the results of the significance test based on the MSPE-adjusted statistics of Clark and West (2007). Conforming to the in-sample performance, the out-of-sample results are significant at the 5% level for most scenarios. At the one-quarter horizon, they are 5.47% and 3.74% respectively for the return spread of VW and EW portfolios, and they increase to 5.35% and 7.86% at the four-quarter horizon. The R^2_{OOS} for the stock-level inflation risk premium are also quite similar.

Table 3.3. Predicting the inflation risk premium

This table reports the results of using nominal-ambiguity correlation (*NAC*) to forecast future cross-sectional inflation risk premium:

$$r^{CSIP}_{t+1:t+h} = a + b_{NAC}\mathbb{I}_{NAC_t>0} + \varepsilon_{t+1:t+h},$$

NAC is computed as the time-varying correlation between shocks to inflation and shocks to ambiguity. The three risk premium measures are in percentage and include the high-minus-low return spreads of value-weighted (VW) and equal-weighted (EW) inflation beta sorted portfolios, and the stock-level risk price estimates (Stock) from the cross-sectional regression. The monthly inflation risk premia within the quarter are compounded to obtain quarterly counterpart, and the forecasting horizons cover from one-quarter to four-quarter. The t-statistics of predictive coefficients b_{NAC} are based on the standard errors of Newey and West (1987) with optimal lag selection following Andrews (1991). IVX-p denotes the p-value of the IVX Wald test of Kostakis et al. (2014) on testing $H_0 : b_{NAC} = 0$ against $H_1 : b_{NAC} \neq 0$. R^2_{IS} is for the in-sample regression, and R^2_{OOS} measures the out-of-sample relative performance of forecasting compared with the historical average model. The significance of R^2_{OOS} is based on the MSPE-adjusted statistic of Clark and West (2007). *, **, *** denote significance at 10%, 5% and 1% level. Data sample ranges from Q3 of 1986 to Q4 of 2017.

Horizon		b_{NAC}	t-stat	IVX- p	R^2_{IS}	R^2_{OOS}
	VW	-4.88	-2.44	0.00	7.44	5.47***
$h=1$	EW	-2.87	-2.31	0.00	5.58	3.74**
	Stock	-2.61	-2.58	0.00	5.90	4.64**
	VW	-3.98	-2.39	0.00	9.81	4.61**
$h=2$	EW	-2.63	-2.46	0.00	8.39	4.92**
	Stock	-2.39	-2.84	0.00	10.67	3.68**
	VW	-3.82	-2.42	0.00	11.87	3.18*
$h=3$	EW	-2.53	-2.43	0.00	10.07	2.59**
	Stock	-2.06	-3.11	0.00	10.35	0.52*
	VW	-3.53	-2.33	0.00	12.25	5.35**
$h=4$	EW	-2.29	-2.30	0.00	10.09	7.86**
	Stock	-1.72	-2.81	0.00	10.19	6.34***

To disentangle the source of predictability, I apply the predictive regression (3.3.6) on each of the decile portfolios. Table 3.4 reports the predictive coefficients together with their t-statistics. While the sign of *NAC* weakly predicts those portfolio returns, the slope coefficients decrease almost monotonically from the lowest to the highest decile portfolio. In particular, those for the lowest value- and equal-weighted portfolio are 1.47 and 0.24, and they all switch to negative values of -3.68 and -3.08 for the highest portfolios respectively. Good inflation hedges have especially low returns when they are also hedgers for the inflation ambiguity, i.e., when $NAC > 0$, and vice versa for the bad inflation hedges. The cross-sectional monotonic pattern leads to the economically large and significant predictive power of *NAC*.

3.3.5 Comparison with alternative explanations

How does the ambiguity channel stands in contrast with the existing resolutions on the inflation risk in the cross-section of stock returns? In this subsection, I evaluate the theoretical and empirical differences with two recent explanations: the conditional ICAPM model of Boons et al. (2017); and the speculative betas of Hong and Sraer (2016) and Li (2016).

In a general setup of ICAPM, Boons et al. (2017) show that the time-varying cross-sectional inflation risk premium should reflect the time-varying predictive relation between inflation and future consumption growth, i.e., the nominal-real covariance (*NRC*). My model extends their rational expectation framework, on which their ICAPM model builds, to allow for inflation model uncertainty or ambiguity. Hence the role of *NAC* should be complementary to the *NRC*. On the other hand, the behavior-based theory proposed by Hong and Sraer (2016) confronts the failure of the classical CAPM model, whose idea is then extended empirically by Li (2016) on understanding the pricing of macroeconomic factors in the cross-section of stock returns.[8] The ambiguity channel differs from their explanations in several respects.

[8] Their channel of speculative betas argues that the fundamentals of stocks with high absolute betas are subject to higher disagreement over the risk factor. The prices of those stocks are likely

Table 3.4. Predictable returns of inflation beta sorted portfolios

This table reports the results of using nominal-ambiguity correlation (*NAC*) to forecast future excess returns of decile portfolio *i*:

$$r^i_{t+1:t+h} = a + b_{NAC}\mathbb{I}_{NAC_t>0} + \varepsilon_{t+1:t+h}.$$

The returns of inflation beta sorted portfolios are in percentage and computed under value-weighted (VW) or equal-weighted (EW) scheme. *NAC* is computed as the time-varying correlation between shocks to inflation and shocks to ambiguity. The monthly returns within the quarter are compounded to obtain quarterly counterpart, and the forecasting horizons cover from one-quarter to four-quarter. The t-statistics of predictive coefficients b_{NAC} are based on the standard errors of Newey and West (1987) with optimal lag selection following Andrews (1991). Data sample ranges from Q3 of 1986 to Q4 of 2017.

	VW				EW			
	$h=1$	$h=2$	$h=3$	$h=4$	$h=1$	$h=2$	$h=3$	$h=4$
L	1.47	1.29	1.03	1.30	0.24	0.45	0.62	1.06
	(0.82)	(0.74)	(0.67)	(0.90)	(0.10)	(0.19)	(0.31)	(0.57)
2	1.23	1.19	0.97	1.29	0.20	0.34	0.45	0.93
	(0.91)	(0.90)	(0.85)	(1.23)	(0.11)	(0.19)	(0.30)	(0.66)
3	0.28	0.26	0.06	0.20	0.06	0.26	0.38	0.79
	(0.21)	(0.20)	(0.05)	(0.18)	(0.04)	(0.18)	(0.31)	(0.68)
4	0.63	0.67	0.56	0.83	0.03	0.17	0.31	0.75
	(0.45)	(0.48)	(0.46)	(0.71)	(0.02)	(0.12)	(0.25)	(0.64)
5	1.22	1.13	0.84	0.99	-0.32	-0.17	-0.10	0.38
	(1.06)	(0.93)	(0.79)	(0.99)	(-0.22)	(-0.12)	(-0.09)	(0.34)
6	-0.06	0.07	-0.17	0.09	-0.46	-0.28	-0.20	0.34
	(-0.04)	(0.06)	(-0.14)	(0.08)	(-0.30)	(-0.19)	(-0.15)	(0.28)
7	0.48	0.49	0.24	0.51	-0.82	-0.63	-0.48	0.10
	(0.33)	(0.34)	(0.19)	(0.42)	(-0.47)	(-0.37)	(-0.34)	(0.07)
8	-0.48	0.02	-0.16	0.07	-1.49	-1.11	-0.85	-0.23
	(-0.28)	(0.01)	(-0.11)	(0.05)	(-0.76)	(-0.59)	(-0.55)	(-0.16)
9	-1.50	-1.26	-1.51	-1.19	-2.41	-2.06	-1.77	-1.06
	(-0.71)	(-0.65)	(-0.89)	(-0.76)	(-1.00)	(-0.89)	(-0.94)	(-0.60)
H	-3.68	-2.95	-3.03	-2.42	-3.08	-2.67	-2.32	-1.59
	(-1.23)	(-1.12)	(-1.30)	(-1.14)	(-1.00)	(-0.94)	(-0.98)	(-0.73)

First, their central predictions are on the absolute betas, which is fine if betas of all

determined by the optimist due to the presence of short-selling constraints. The mispricing will then counteract the usual risk-return relation, and higher disagreement leads to larger counteracting effect.

cross-sectional portfolios share the same sign. However, it is clear from Table 3.1 that the inflation beta sorted portfolios under the value-weighted schemes have negative and positive inflation betas. Thus the behavioral theory is agnostic to explain that cross-section of assets. Second, their key predictor is the macro disagreement, while the model in this paper points to the use of *NAC*.

To empirically compare the ambiguity-based predictor with variables mentioned above. I first obtain the quarterly *NRC* measure, and the inflation disagreement $(Disp)$ as the forecast dispersion of one-quarter ahead inflation from SPF. Then I run the following bivariate predictive regression:

$$r^{CSIP}_{t+1:t+h} = a + b_{NAC}\mathbb{I}_{NAC_t>0} + b_X X_t + \varepsilon_{t+1:t+h}, \tag{3.3.8}$$

where the control variable X_t is selected from $\{\mathbb{I}_{NRC_t>0}, NRC_t, Disp_t\}$. I consider both the original *NRC* and its sign dummy.[9], and the regression results are tabulated in Table 3.5.

The first observation is that the positive predictive coefficients of the *NRC* and the sign dummy line up well with the ICAPM model and conclusions from Boons et al. (2017), though they are marginally significant and can only explain the inflation risk among value-weighted portfolios. Meanwhile, the explanatory power of *NAC* is robust for all risk premia considered. We note that its predictive coefficients are less significant after adding the original *NRC*, yet they remain significant when considering the sign dummy of *NRC*. This may be due to the noisier estimates of the predictive coefficients of *NAC* after adding in the additional regressor *NRC*, which itself is also contaminated with nontrivial estimation error.

Interestingly, the forecast dispersion as dictated by the theory of speculative betas only displays the predictive ability for risk premium estimates from equal-weighted portfolio and stock-level returns. This seems to suggest that the risk-based and the behavioral-based theories capture different aspects of cross-sectional infla-

[9]The replicated *NRC* is plotted in Figure A.5 in the Internet Appendix. We note that the original estimates of Boons et al. (2017) is based on monthly data, while the replicated series is based on the quarterly data.

tion risk premia. Simultaneously, we note that the predictive power of *NAC* declines at some scenarios, especially for the equal-weighted portfolio returns after adding in the forecast dispersion. This may stem from the potential positive link between the ambiguity premium and the magnitude of forecast dispersion (see e.g. Drechsler, 2013). The overlapping information could lead to lower statistical significance of *NAC*. However, they are still different forces, as captured by the nontrivial improvement of adjusted R^2 in many cases, and the incapability of forecast dispersion on reconciling the inflation risk premium from value-weighted returns. Overall, the nominal-ambiguity correlation as motivated by the ambiguity theory provides a unified explanation, and the predictability is unlikely to be subsumed by existing resolutions.

3.3.6 Industry-level evidence

In addition to the inflation risk premium from the full cross-section of individual stocks, understanding how the inflation risk premium varies across different industries and sectors is equally important (see e.g. Lu, 2008; Ang et al., 2012; Eraker et al., 2016). In this subsection, I evaluate the empirical relevance of the ambiguity channel on the industry-level pricing of inflation risk. I focus on ten industries as classified by Kenneth French, where I first obtain three measures of *CSIP* analogously as before within each industry.[10] At the end of month t, I form 10 portfolios within each industry by sorting on the inflation betas. The portfolio returns are computed similarly using equal- or value-weighted scheme. To obtain the stock-level estimates for some industry j, I run the stock-level cross-sectional regression within that industry:

$$r_{t+1}^{ei,j} = \hat{\beta}_{mkt,t}^{i,j}\lambda_{mkt,t}^{j} + \hat{\beta}_{\pi,t}^{i,j}\lambda_{\pi,t}^{j} + \varepsilon_{t+1}^{i,j}, \quad i = 1, 2, \ldots N_{j,t}, \tag{3.3.9}$$

[10]Ten industries cover the Nondurable, Durable, Manufacturing, Energy, Hi-tech, Telecoms, Shops, Health, Utilities and Other.

Table 3.5. Comparison with other predictors

This table reports the results of the bivariate predictive regression:

$$r^{CSIP}_{t+1:t+h} = a_0 + b_{NAC}\mathbb{I}_{NAC_t>0} + b_X X_t + \varepsilon_{t+1:t+h},$$

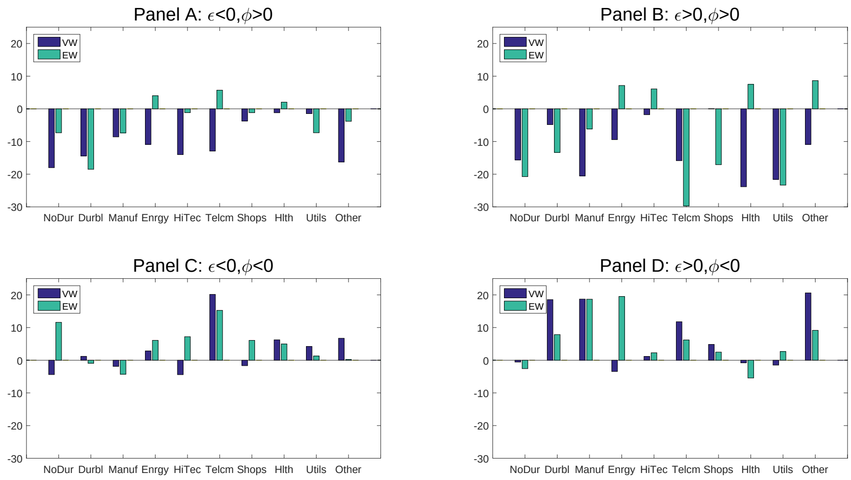
where X_t is *NRC* of Boons et al. (2017) or the inflation forecast dispersion of Li (2016). The three risk premium measures are in percentage and include the high-minus-low return spreads of value-weighted (VW) and equal-weighted (EW) inflation beta sorted portfolios, and the stock-level risk price estimates (Stock) from the cross-sectional regression. The t-statistics of predictive coefficients are in parentheses and based on the standard errors of Newey and West (1987) with optimal lag selection following Andrews (1991). The forecasting horizons cover one-quarter to four-quarter. $Adj.R^2$ $(control)$ reports the adjusted R^2 from the regression by using either of the control variables as the single predictor, and $Adj.R^2$ reports that from the regression of using both *NAC* and the control variable. Data sample ranges from Q3 of 1986 to Q4 of 2017.

	VW			EW			Stock		
Panel A: $h=1$									
$\mathbb{I}_{NRC>0}$	1.11			0.48			0.49		
	(1.42)			(0.85)			(0.93)		
NRC		1.08			0.15			0.03	
		(0.98)			(0.20)			(0.05)	
$Disp$			0.21			1.04			0.69
			(0.37)			(2.11)			(1.61)
NAC	-2.13	-1.94	-2.36	-1.30	-1.37	-1.03	-1.17	-1.30	-1.04
	(-2.16)	(-1.65)	(-2.26)	(-2.06)	(-1.96)	(-1.51)	(-2.26)	(-2.05)	(-2.15)
$Adj.R^2$ (control)	2.87	4.16	0.79	1.15	0.88	4.82	1.52	0.58	3.34
$Adj.R^2$	7.37	7.08	7.08	4.62	4.07	4.07	5.14	4.36	4.36
Panel B: $h=2$									
$\mathbb{I}_{NRC>0}$	1.21			0.31			0.18		
	(1.72)			(0.65)			(0.44)		
NRC		1.63			0.39			0.22	
		(1.76)			(0.60)			(0.56)	
$Disp$			-0.12			1.03			0.95
			(-0.21)			(2.04)			(1.64)
NAC	-1.65	-1.23	-2.04	-1.23	-1.14	-0.91	-1.14	-1.09	-0.82
	(-2.05)	(-1.37)	(-2.25)	(-2.15)	(-2.09)	(-1.54)	(-2.34)	(-2.23)	(-2.37)
$Adj.R^2$ (control)	6.27	11.29	0.34	1.30	3.31	8.62	1.15	3.22	11.43
$Adj.R^2$	11.73	13.54	13.54	7.30	7.46	7.46	9.43	9.49	9.49
Panel C: $h=3$									
$\mathbb{I}_{NRC>0}$	0.83			0.22			0.30		
	(1.48)			(0.57)			(0.95)		
NRC		1.64			0.45			0.37	
		(1.96)			(0.74)			(1.11)	
$Disp$			-0.39			0.68			0.94
			(-0.92)			(1.36)			(1.59)
NAC	-1.67	-1.14	-2.07	-1.20	-1.06	-1.00	-0.94	-0.86	-0.65
	(-2.19)	(-1.42)	(-2.47)	(-2.22)	(-2.28)	(-1.69)	(-2.61)	(-2.45)	(-1.95)
$Adj.R^2$ (control)	4.91	14.82	-0.21	1.28	4.80	6.50	2.40	5.03	13.45
$Adj.R^2$	12.51	17.47	17.47	8.87	9.58	9.58	9.66	9.93	9.93
Panel D: $h=4$									
$\mathbb{I}_{NRC>0}$	1.04			0.38			0.42		
	(1.80)			(0.99)			(1.51)		
NRC		1.64			0.49			0.48	
		(1.93)			(0.78)			(1.35)	
$Disp$			-0.31			0.66			0.92
			(-0.70)			(1.35)			(1.62)
NAC	-1.46	-0.99	-1.89	-1.04	-0.91	-0.88	-0.74	-0.64	-0.50
	(-2.07)	(-1.26)	(-2.39)	(-2.04)	(-2.03)	(-1.57)	(-2.26)	(-1.82)	(-1.33)
$Adj.R^2$ (control)	7.75	17.06	-0.09	2.75	5.76	7.18	4.83	7.59	16.54
$Adj.R^2$	14.81	19.40	19.40	9.62	10.07	10.07	11.00	11.21	11.21

where $N_{j,t}$ is the number of stocks with non-missing inflation betas at month t and returns at month $t+1$ in the industry j. The stock-level risk premia are then scaled by the post-formation betas within each industry.

Figure 3.4. State-dependent inflation risk prices for industries

This figure displays the conditional average of annualized inflation risk premia of 10 industries. The two inflation risk premium measures are excess returns in percentage of high-minus-low equal-weighted (EW) and value-weighted (VW) portfolios. The average returns are computed over four regimes characterized by the signs of *NRC* (ε) and *NAC* (ϕ), based on the monthly data in the following quarter. Data sample ranges from October 1986 to December 2017.



As the first-step qualitative analysis at industry-level, I extend the results in Figure 3.3 to 10 industries. For each industry and within each quadrant characterized by the signs of (ε, ϕ), I calculate the average high-minus-low return spread of value- and equal-weighted portfolios. Figure 3.4 plots the results for four quadrants.[11] Remarkably, the time-variations in the inflation risk premia at the industry-level also conform to the sign of *NAC*. When *NAC* is positive (negative), almost all industry-level inflation risk premia are negative (positive). Even though some industries such as Energy or Technology are typically regarded as good inflation hedge (Ang et al., 2012; Boons et al., 2017), the dynamics of their inflation risk premia admit common fluctuations with all other industries according to the sign of *NAC*. This is consistent with the theoretical argument that the ambiguity channel should be pervasive and not restricted in any specific industry.

Turning to the statistical test, I run the predictive regression (3.3.6) industry-by-industry. In Table 3.6, I report the estimated predictive coefficients and the post-

[11] The results based on the stock-level estimates are similar and hence omitted for the interest of space.

formation inflation betas of high-minus-low portfolios within each industry. The evidence suggests that the beta spreads are significant in many industries such as the Energy and the Hi-Tech, whose stocks should be tightly linked to the fluctuating inflation. Furthermore, the negative predictability by *NAC* is maintained for almost all industry-level inflation risk premia, and the portion of significant predictive coefficients is nontrivial. Notably, the economic consequence of sign switch in *NAC* is sizable. For instance, positive *NAC* at the current quarter predicts in the following quarter the losses of -3.14% and -4.91% in the quarterly return spreads of value-weighted portfolios in nondurable and durable sectors.

To gain statistical power, I pool the three inflation risk premium measures from each industry to form in total 30 industry-level estimates, and then I run the following panel regressions:

$$r^i_{t+1:t+h} = \alpha + \beta_D \mathbb{I}_{NAC_t>0} + \beta_X X_t + \varepsilon^i_{t+1:t+h}, \tag{3.3.10}$$

$$r^i_{t+1:t+h} = \alpha + \beta_{NAC} NAC_t + \beta_X X_t + \varepsilon^i_{t+1:t+h}, \tag{3.3.11}$$

where I consider both the original *NAC* and its sign dummy as predictors, and the potential control variables X_t are the *NRC* and forecast dispersion as discussed before. The regressions are carried out by adding fixed-effect, and the statistical significance is tested via the standard errors of Driscoll and Kraay (1998) that are robust to general form of temporal and spatial dependence.

Panel A of Table 3.7 reports the results. The negative predictive coefficients are significant for all horizons, even after controlling for the competing effects. The results are consistent with those from the aggregate-level *CSIP*. However, the coefficients of *NRC* and forecast dispersion are insignificant, and R^2 remains almost unchanged after adding in these two variables. This is due to the their weak explanatory power on different risk premium estimates from value-weighted or equal-weighted portfolios. To further test the unified explanation, in Panel B, I pool 30 industry-level inflation risk premium estimates with 3 measures obtained from all

Table 3.6. Predicting the industry-level inflation risk premia

This table reports the post-formation high-minus-low inflation beta spreads from decile portfolios formed in each industry, and are obtained by estimating the following equation using the full-sample monthly returns of high-minus-low portfolio within industry j:

$$r_{jt}^{HML} = \alpha_j + \beta_{jm} MKT_t + \beta_{post,j}^{HML} u_t^{\pi} + \zeta_t,$$

where MKT_t is the market factor, and u_t^{π} is the inflation shock. The table also reports the results of using nominal-ambiguity correlation (NAC) to forecast future cross-sectional inflation risk premium within each industry j:

$$r_{t+1}^{CSIP,j} = a_j + b_{NAC,j} \mathbb{I}_{NAC_t > 0} + \varepsilon_{t+1},$$

NAC is computed as the time-varying correlation between shocks to inflation and shocks to ambiguity. The three risk premium measures are in percentage and include the high-minus-low return spreads of value-weighted (VW) and equal-weighted (EW) inflation beta sorted portfolios, and the stock-level risk price estimates (Stock) from the cross-sectional regression. These three measures are obtained within each industry. The monthly inflation risk premia within the quarter are compounded to obtain quarterly counterpart. All t-statistics are in parentheses and based on the standard errors of Newey and West (1987) with optimal lag selection following Andrews (1991). Data sample ranges from Q3 of 1986 to Q4 of 2017.

	VW			EW			Stock		
	β_{post}^{HML}	NAC	$R^2(\%)$	β_{post}^{HML}	NAC	$R^2(\%)$	β_{post}^{HML}	NAC	$R^2(\%)$
Nondurable	3.58	-3.14	1.48	1.60	-4.02	3.69	0.09	-7.17	6.56
	(2.92)	(-1.30)		(1.05)	(-2.44)		(2.37)	(-3.12)	
Durable	3.43	-4.91	1.92	0.31	-4.63	1.76	0.04	-0.30	0.67
	(1.47)	(-1.60)		(0.15)	(-1.52)		(0.45)	(-0.82)	
Manufacturing	2.63	-4.17	3.02	2.09	-2.83	3.11	0.09	-8.14	4.85
	(3.54)	(-1.62)		(1.82)	(-1.82)		(2.67)	(-2.50)	
Energy	7.63	-2.93	0.81	5.61	-1.82	0.47	0.23	-9.72	1.01
	(4.60)	(-0.94)		(3.79)	(-0.73)		(4.01)	(-0.99)	
Hi-Tech	2.07	-2.29	1.13	1.38	-1.19	0.52	0.06	-3.91	2.21
	(2.26)	(-1.13)		(1.22)	(-0.74)		(2.78)	(-1.73)	
Telecom	-0.26	-9.11	3.90	0.22	-2.98	0.47	-0.05	0.11	0.15
	(-0.08)	(-2.14)		(0.07)	(-0.89)		(-0.84)	(0.42)	
Shops	3.03	-0.73	0.11	1.38	-1.78	0.93	0.04	-2.04	1.34
	(2.60)	(-0.33)		(0.92)	(-1.12)		(0.95)	(-1.35)	
Health	-0.37	-2.68	0.93	-2.29	0.50	0.03	0.02	-6.21	1.86
	(-0.25)	(-1.11)		(-0.93)	(0.18)		(0.61)	(-1.28)	
Utilities	3.92	-1.34	0.36	2.87	-2.38	1.32	0.24	-6.18	1.10
	(3.20)	(-0.57)		(2.61)	(-1.10)		(3.63)	(-1.12)	
Other	2.70	-6.94	12.96	3.23	-1.34	0.93	0.08	-8.76	1.52
	(3.40)	(-3.68)		(2.88)	(-1.10)		(2.81)	(-1.93)	

individual stocks. Evidently, adding in other estimates of *CSIP* does not affect the negative and significant explanatory power. As a final check, Panel C gives the results by using the original *NAC* as the predictor. Although the statistical significance slightly weakens, possibly due to larger estimation error of the predictor, the slope coefficients are still significant. In all, the sign changes in *NAC* provides a satisfactory resolution to the time-varying cross-sectional inflation risk premium, both at the aggregate-level and at the industry-level.

3.4 Additional Results and Robustness Checks

This section lays out further empirical implications and provides a battery of robustness checks. The full-detailed results for robustness can be found on the Internet Appendix.

3.4.1 Market timing strategies

Given the substantial explanatory power of *NAC*, I now evaluate whether there is real-time benefit of using *NAC* to guide the investment on the inflation risk. To this end, I study the performance of three strategies. The first strategy is the zero-cost investment of buying the portfolio with the lowest inflation betas and shorting that with the highest inflation betas. This is an unconditional strategy implementing the usual wisdom that the investor dislikes inflation since it signals bad news for future consumption growth (e.g. Piazzesi et al., 2006), and hence is negatively priced. The second strategy is a market-timing strategy based on the sign of nominal-real covariance NRC_t, motivated by Boons et al. (2017). At the end of quarter t, the investor follows the first strategy unless when the NRC_t becomes positive, she then swaps the long-short positions. Clearly, such trade aims to benefit from the variations of the inflation risk price as dictated by the conditional ICAPM model. The third strategy relies on the market timing of nominal-ambiguity correlation NAC_t, by swapping the long-short portfolios when $NAC_t < 0$ following Proposition 2. The

Table 3.7. Panel regression of cross-sectional inflation risk premia

This table reports the results of panel regressions:

$$r^i_{t+1:t+h} = \alpha + \beta_D \mathbb{I}_{NAC_t>0} + \beta_X X_t + \varepsilon^i_{t+1:t+h},$$
$$r^i_{t+1:t+h} = \alpha + \beta_{NAC} NAC_t + \beta_X X_t + \varepsilon^i_{t+1:t+h},$$

where X_t is *NRC* of Boons et al. (2017) or the inflation forecast dispersion of Li (2016), and both the sign dummy and originally estimated *NAC* are considered. The regressions are estimated by adding fixed-effect and by pooling 30 industry-level measures (Panel A), and further 3 aggregate-level measures (Panel B) for the cross-sectional inflation risk premium. Panel C uses the original estimates of *NAC* as the predictor. All risk premium estimates are in percentage. The forecasting horizon ranges from one-quarter to four-quarter. The nominal-real covariance (*NRC*) and ambiguity level are added as control variables. The t-statistics are in parentheses and based on the asymptotic Driscoll and Kraay (1998) standard errors with lag h. Data sample ranges from Q3 of 1986 to Q4 of 2017.

	h=1			h=2			h=3			h=4		
Panel A: 10 industries (dummy)												
NAC	-1.01	-1.00	-0.94	-0.93	-0.88	-0.86	-0.82	-0.76	-0.79	-0.73	-0.69	-0.70
	(-2.93)	(-2.54)	(-2.64)	(-2.97)	(-2.61)	(-2.57)	(-2.90)	(-2.79)	(-2.60)	(-2.76)	(-2.69)	(-2.31)
NRC		0.01			0.09			0.11			0.09	
		(0.01)			(0.25)			(0.35)			(0.26)	
Disp			0.16			0.18			0.06			0.09
			(0.44)			(0.49)			(0.17)			(0.28)
$R^2(\%)$	0.82	0.82	0.84	1.35	1.36	1.39	1.58	1.60	1.58	1.69	1.71	1.71
Nobs	3750	3750	3750	3720	3720	3720	3690	3690	3690	3660	3660	3660
Panel B: 10 industries +Aggregate (dummy)												
NAC	-1.03	-1.01	-0.96	-0.94	-0.88	-0.87	-0.84	-0.76	-0.82	-0.76	-0.69	-0.72
	(-2.97)	(-2.51)	(-2.63)	(-2.99)	(-2.44)	(-2.52)	(-2.90)	(-2.71)	(-2.61)	(-2.76)	(-2.59)	(-2.33)
NRC		0.09			0.51			0.69			0.65	
		(0.09)			(0.37)			(0.49)			(0.41)	
Disp			0.19			0.19			0.06			0.09
			(0.50)			(0.56)			(0.18)			(0.29)
$R^2(\%)$	0.92	0.92	0.95	1.49	1.51	1.54	1.76	1.81	1.77	1.89	1.94	1.91
Nobs	4125	4125	4125	4092	4092	4092	4059	4059	4059	4026	4026	4026
Panel C: 10 industries +Aggregate (raw)												
NAC	-0.83	-0.74	-0.72	-0.82	-0.72	-0.73	-0.73	-0.62	-0.68	-0.64	-0.55	-0.59
	(-2.80)	(-2.17)	(-2.32)	(-2.75)	(-2.22)	(-2.42)	(-2.63)	(-2.18)	(-2.44)	(-2.48)	(-2.03)	(-2.18)
NRC		0.22			0.26			0.27			0.24	
		(0.57)			(0.75)			(0.78)			(0.67)	
Disp			0.28			0.25			0.12			0.15
			(0.73)			(0.76)			(0.42)			(0.55)
$R^2(\%)$	0.60	0.63	0.66	1.15	1.25	1.25	1.36	1.51	1.39	1.41	1.58	1.47
Nobs	4125	4125	4125	4092	4092	4092	4059	4059	4059	4026	4026	4026

performance of this strategy is important since it concerns the economic relevance of the ambiguity channel discussed in this paper.

The summary statistics of returns to these strategies are listed in Table 3.8. First, the unconditional strategy performs poorly under either value- or equal-weighted portfolios, with annualized average excess returns of only 1.04% and -1.20% respectively. The abnormal returns after controlling for the CAPM, Fama-Fren three- or five-factor yield similarly insignificant results. Second, incorporating the information in the *NRC* improves the performance substantially for the value-weighted portfolios. The strategy yields an annualized mean excess return of 5.87%, which is significant at the 10% level. However, the abnormal return is only 2.34% after controlling for the Fama-French five-factor model. Meanwhile, the improvement for the equal-weighted portfolios by conditioning on *NRC* is at most marginal, from -1.20% to 1.85%. The strategy though generates positive excess returns, the value is still comparably small, and the abnormal return is even negative under Fama-French five-factor model. The performance thus is consistent with the results of predictive regressions as shown in Table 3.5.

For the strategy using *NAC*, the economic benefit is large. Trading on the value-weighted portfolios based on the information of *NAC* delivers an annualized mean excess return of 9.58%, with a t-statistic of 2.70. The annualized Sharpe ratio is 0.59, which slightly outperforms that for the U.S. aggregate stock market (0.54). Moreover, the abnormal returns are robustly large and significant. Even controlling for the Fama-French five-factor model, the abnormal return remains almost unchanged at 8.93%. Besides, the long-short strategy on the equal-weighted portfolios also benefits from conditioning on *NAC*. The average annualized return reaches 5.77% with a t-statistic of 2.42, and the abnormal return is still significant at 10% level under Fama-French five-factor model.

To show the consistency of strategy profitability, I plot their cumulative returns starting from October 1986 to December 2017 in Figure 3.5. The pattern basically mimics the results from Table 3.8, with the strategy based on *NAC* performing considerably better. The unconditional strategy though shows some improvement around 2001, the overall performance is dismal. The conditional strategy based on *NRC* shows large improvement for value-weighted portfolios. However, its usefulness decreases dramatically over the past decade, as clearly seen from the almost flat

Table 3.8. Market-timing and returns from trading on inflation risk

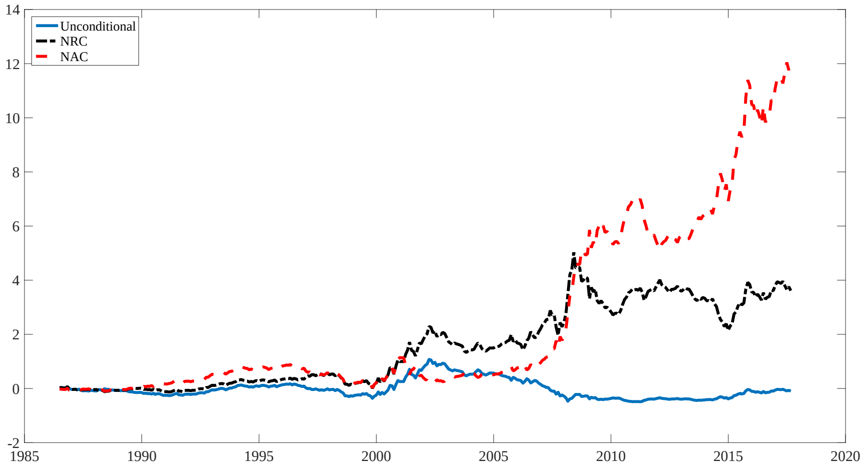
This table reports the statistics of returns to three strategies on trading the inflation beta sorted portfolios (value- and equal-weighted). The first strategy (Uncon.) denotes the unconditional strategy of buying the portfolio with the lowest and shorting that with the highest inflation beta. The second strategy (*NRC*) follows the first one except that the long-short positions are swapped when *NRC* becomes positive. The third strategy (*NAC*) follows the first one except that the long-short positions are swapped when *NAC* becomes negative. The annualized average excess returns, volatilities and Sharpe ratios are reported. The annualized abnormal returns (alpha) of portfolio excess returns are based on the CAPM, Fama-French three-factor and five-factor models. The Newey-West t-statistics are in parentheses. Data sample ranges from October 1986 to December 2017.

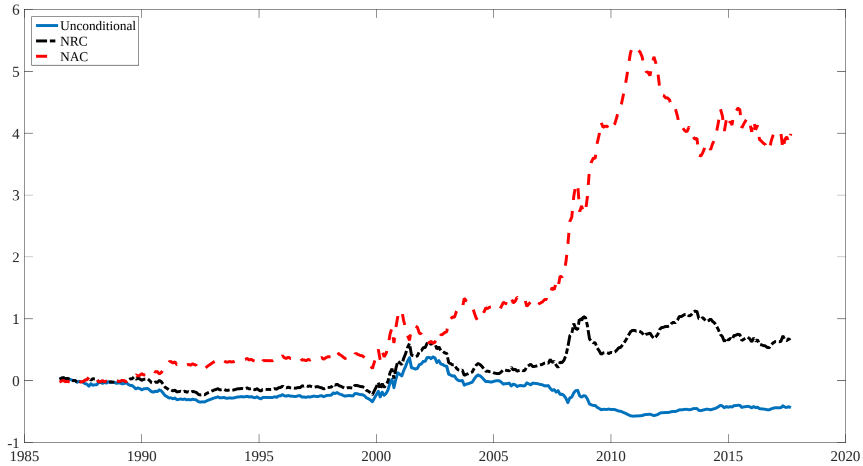
	Value-weighted			Equal-weighted		
	Uncon.	*NRC*	*NAC*	Uncon.	*NRC*	*NAC*
Excess return (%)	1.04	5.87	9.58	-1.20	1.85	5.77
	(0.34)	(1.76)	(2.70)	(-0.54)	(0.77)	(2.42)
Volatility (%)	16.55	16.53	16.32	11.35	11.43	11.23
Sharpe ratio	0.06	0.36	0.59	-0.11	0.16	0.51
Skewness	0.28	0.54	0.49	0.22	0.36	0.62
Kurtosis	5.72	5.51	5.57	7.36	7.16	7.16
CAPM alpha (%)	3.54	7.93	10.60	0.36	3.43	6.37
	(1.09)	(2.30)	(2.83)	(0.15)	(1.40)	(2.49)
FF-3F alpha (%)	1.75	6.30	9.63	-0.88	2.12	5.37
	(0.59)	(2.02)	(2.65)	(-0.45)	(1.01)	(2.35)
FF-5F alpha (%)	-2.23	2.34	8.93	-4.16	-0.77	4.19
	(-0.78)	(0.80)	(2.70)	(-2.04)	(-0.35)	(1.87)

cumulative returns during the post-crisis periods. Instead, the information in *NAC* remains stable and powerful throughout the sample compared with other strategies, for both value- and equal-weighted portfolios.

Figure 3.5. Cumulative returns of trading on inflation risk

This figure plots the cumulative excess returns to three strategies trading on the inflation beta sorted portfolios (value- and equal-weighted). The first strategy (Unconditional) denotes the unconditional strategy of buying the portfolio with the lowest and shorting that with the highest inflation beta. The second strategy (*NRC*) follows the first one except that the long-short positions are swapped when *NRC* becomes positive. The third strategy (*NAC*) follows the first one except that the long-short positions are swapped when *NAC* becomes negative. Data sample ranges from October 1986 to December 2017.





3.4.2 Alternative estimates of *NAC*

Below I carry out a series of robustness checks. Since the main findings rely on the performance of nominal-ambiguity correlation, I thus evaluate the predictability from other ways of estimating *NAC*. More specifically, I experiment with other *NAC* measures which either build on the correlation of levels instead of shocks, or are obtained under different sizes of rolling-window. That is, I change the 20-quarter to 12- and 16-quarter rolling-window. These different measures are plotted in Figure A.4. Given the non-trivial deviations from the baseline implementation, the *NAC* obtained under different ways still show significant co-movements with the benchmark *NAC*. I then use those *NACs* to predict future cross-sectional inflation risk premium. Table A.7 documents the results. While the evidence from using the level-based estimate does not change materially, using shorter window size to estimate *NAC* makes the result noisier. The p-values from the IVX-Wald test of Kostakis et al. (2014) are around 0.1 for the value-weighted portfolio returns. This is not surprising because the *NAC* is estimated with only 12 or 16 quarters and hence the estimation errors are comparably larger than the 5-year window size. Even so, it is worthwhile pointing out that all predictive coefficients remain negative, and those for the equal-weighted portfolio and stock-level estimates remain highly significant. In addition, the out-of-sample R^2 are positive for many scenarios. The evidence thus suggests that the main empirical results are stable and robust.

3.4.3 More controls when estimating inflation betas

In the benchmark implementation, the inflation betas are estimated according to Equation (3.3.2) by controlling for the market factor. Table A.8 presents the results of predictive regression (3.3.6) when inflation betas are estimated under other conventional controls. Similar to Table 3.3, I also report the p-value of the IVX-Wald test of Kostakis et al. (2014) when testing the significance of b_{NAC}. Basically, even the inflation betas are obtained after controlling for the Fama-French three-factor, Carhart four-factor, and the Fama-French five-factor, the cross-sectional inflation risk premium is still highly predictable by the sign of *NAC*. Most of the in-sample and out-of-sample results are significant and similar to those in Table 3.3.

3.4.4 More controls when testing the predictive power

The previous comparisons with the ICAPM resolution of Boons et al. (2017) are all based on the quarterly data. However, their original estimate of *NRC* rely on the monthly data of inflation and consumption growth. Since comparing the empirical magnitudes of *NAC* and *NRC* is crucial, I re-estimate Equation (3.3.3) with a 60-month rolling window using monthly inflation and consumption growth data. More data points at higher-frequency may help improve the accuracy of estimated *NRC* and thus its performance on driving the inflation risk premium. To convert the monthly estimates to quarterly frequency in order to carry out the predictive regression, I treat either the monthly *NRC* at the end of each quarter (NRC_1), or the within-quarter average of *NRC* (NRC_2) as the quarterly counterpart. These monthly-based measures are plotted in Figure A.5 together with the benchmark *NRC*. While the three estimates show substantially co-movements, the quarterly-based estimates are more volatile, which may be due to less data used for estimation (20 quarter-s). Then I test the predictive power of *NAC* jointly with monthly-based *NRC* in Table A.9. Clearly, no matter which way of aggregation to obtain quarterly *NRC*, the monthly-based *NRC* estimates do not outperform *NAC* in terms of forecasting future *CSIP*.

In addition, I add more control variables to better understand the unique linkage between *NAC* and the cross-sectional inflation risk premium. It is reasonable to conjecture that the compensation for the inflation risk is tied to the aggregate-level risk premium. I hence rely on a large collection of state variables that are well-known predictors for aggregate risk premium, as surveyed by Welch and Goyal (2007).[12] The results of bivariate regressions by using the sign dummy of *NAC* and

[12]The data are available from October 1986 to December 2016. The details of those predictors can be found in their original paper.

one of the 16 predictors are presented in Table A.10, where I report the t-statistics of Newey and West (1987) adjusted with the optimal lag selection following Andrews (1991). The consensus from the table is that the predictive ability of *NAC* is robustly strong, no matter what controls are added in. Perhaps surprisingly, the explanatory ability of most well-known predictors are small even under those in-sample tests. This highlights the importance of uncovering the detailed channel of inflation risk compensation in the cross-section of stock returns, which seems to be segmented from the aggregate stock market risk.

3.4.5 Measures for inflation risk

As final robustness checks, I consider different choices of candidate risk factor used. There is a long tradition in the empirical asset pricing literature that instead of focusing on the raw risk factors, it usually helps to construct the so-called *factor-mimicking portfolio* in order to transform the non-traded factor to traded factor (see e.g. Breeden, 1979; Li, 2016). The construction relies on the simple projection of the candidate risk factor on a set of asset returns, which are called the *base assets*, and then treats the fitted part as the risk factor. However, despite the popularity of the method, the suitability of using factor-mimicking portfolio is not uncontroversial (Jiang et al., 2015).

To understand whether my results are sensitive to either of the ways implemented by the literature, I construct the factor-mimicking portfolio for inflation shocks, and I estimate firm-level betas with respect to the returns of the mimicking portfolio. For the choice of base assets I follow most of the prior literature (see e.g. Lewellen et al., 2010) by choosing the 25 size and book-to-market sorted portfolios, 25 size and momentum portfolios, the value-weighted market portfolio, and 10 industry portfolios as classified by Kenneth French. To begin with, I run the following linear projection of inflation shock at month t on the vector of excess returns of base assets w_t:

$$u_t^{\pi} = \alpha_{\pi} + \beta_{\pi} w_t + \varepsilon_t, \tag{3.4.1}$$

then I form decile portfolios based on individual stock's sensitivity to the fitted term $\hat{\beta}_{\pi} w_t$. Panel A of Table A.11 reports the results of the panel regression (3.3.10b) by pooling 3 aggregate-level inflation risk premium estimates, and by adding either *NRC* or the macro dispersion as the control variable. The t-statistics though are somewhat smaller, they are still negative and significant at the 10% level after controlling for the effect of macro dispersion. The results further point to differences between channels of ambiguity and speculative betas.

As an alternative measure for inflation risk, instead of using the inflation shock, I use the raw inflation series following Bekaert and Wang (2010) and Ang et al. (2012). Focusing on the original series removes the concern on the potential misspecification of Equation (3.3.1) used to obtain the inflation shocks. Also, no estimation error will be introduced into the risk factor. The results of the same panel regression are in Panel B of Table A.11. Obviously, the strong predictive power is similar, and the pattern is quantitatively similar with those using the inflation shocks.

3.5 Conclusion

This paper documents the importance of ambiguity premium on the pricing of inflation risk among individual stocks. This component is new and well motivated by a consumption-based asset pricing model with inflation non-neutrality and ambiguity-averse investor. The model predicts that the individual stock's inflation beta and ambiguity beta are essentially linked. The endogenous connection together with the realistic co-movement of inflation and its ambiguity generates complicated dynamics of cross-sectional inflation risk premium, which sheds light on the prior puzzling evidence that the inflation risk in the stock market is insignificant priced.

I find novel empirical results that match well with the theoretical predictions. First, the ambiguity beta and inflation beta are indeed significantly linked. Even though their relation is subject to substantial time-variations, those variations are roughly consistent with the movement of economy-wide regimes, as predicted by the model. Moreover, the ambiguity channel itself explains a large part of future cross-sectional inflation risk premium. The nominal-ambiguity correlation (*NAC*), which essentially controls how ambiguity premium affects the pricing of inflation risk, significantly predicts the cross-sectional inflation risk premium. The predictive power is robust under many different specifications and multiple evaluation criteria. The economic value of relying on *NAC* to trade on the inflation risk from the individual stocks is also large. The market-timing strategy based on the sign of *NAC* delivers annualized abnormal returns under the Fama-French five-factor model of 8.93% and 4.19% respectively, for value- and equal-weighted portfolios.

I emphasize that the ambiguity channel is distinct from the resolutions provided by earlier literature. First, my study in fact extends the ICAPM framework discussed in Boons et al. (2017). The ambiguity premium does not exist in their framework with rational expectation. Second, though the ambiguity channel is related to the behavioral-based explanation proposed by Hong and Sraer (2016) and Li (2016), the model and empirical implications are sharply different. My model mainly predicts that the sign of nominal-ambiguity correlation matters, while they suggest that the high disagreement over inflation should be important. Moreover, after putting these competing alternatives in a unified empirical framework, I find that the ambiguity channel significantly dominates them in terms of predicting the cross-sectional inflation risk premium.

Chapter 4 The Share of Systematic Risk in Foreign Exchange and Stock Markets

4.1 Introduction

Uncovering common sources of systematic risk from different markets is of crucial importance for international asset pricing and policy analysis. A rich strand of the literature has documented the integration of the stock markets around the world (see a recent review by Lewis (2011)). If stock markets of different countries are not segmented, the equilibrium equity price is partially determined by a world common stochastic discount factor (SDF). Intuitively, this same logic should also line up the financial markets of different asset classes. However, unlike the relatively consistent results on the relation between different stock markets, the empirical evidence on the share of systematic risk between the foreign exchange and the stock market is mixed. For example, Jorion (1991) finds that the currency risk is almost negligible in the stock market, whereas Carrieri et al. (2006) reports the significant currency risk premium. In particular, a recent paper by Burnside (2012) finds that the successful factor models in the literature that have been shown to well explain one market have little explanatory power for the other market. Such empirical results are puzzling since if a risk factor based on one market is indeed informative about the stochastic discount factor of investors, then it should also have pricing implications for other markets.

Instead of directly examining the well-established risk factors in the currency or the stock market, in this paper I use a different strategy in that I search for the plausible factor through an affine term structure model of interest rate and exchange rate. Such a model has received much attention in modeling the bond yield (see e.g. Ang and Piazzesi (2003)) and there is growing interest in extending it to describing the exchange rate (see e.g. Backus et al. (2001) and Anderson et al. (2010)). The common objective of using the model is to evaluate the impact of the observable or latent states, which may be relevant to the SDF, on the bond yields and exchange rates. However, here I shift my focus to study the usefulness of the underlying states of SDF in explaining the stock market.

The goal of this paper is twofold. First, I propose and estimate an affine model of the joint dynamics of exchange rate and interest rate. In addition to the commonly used risk factors for capturing the bond yield movements, I use a latent state to capture the fluctuations of the exchange rate and the implied variance from currency options. I evaluate the empirical performance of such a model and discuss how bond risk factors and the latent state affect the exchange rate and the currency options. Second and more importantly, I examine whether this extracted latent state from the foreign exchange market is an important risk factor for the stock market following a large literature on the stock return predictability (see e.g. Welch and Goyal (2008)). Not only I test whether the latent state is a significant driver of the time-varying expected return of the aggregate stock market, but also I discuss its relevance in explaining the cross-sectional return differences of the industry portfolios.

I find that the latent factor in the estimated SDF, which I term as the *Forex-specific factor*, turns out to be a strong predictor of the home and foreign country aggregate stock market risk premia.[1] The slope coefficient of the predictive regression for home (foreign) market is -0.97% (-0.67%), with a t-statistic 2.72 (2.28) and adjusted R^2 4.16% (2.15%). Moreover, the predictability is statistically significant for most horizons ranging from 1-month to 36-month. For home (foreign) market, the adjusted R^2 changes from 3.83% (2.15%) for two-year (one-month) to 9.51% (12.5%) for three-month (three-year) horizon. Such a factor is also important

[1]The data of Forex-specific factor is available upon request

in driving the time-varying expected return of different industry and characteristic portfolios, which have been shown by many papers to have distinct risk profiles (see e.g. Petkova (2006)). The predictive power is significant for 8 out of 10 industry portfolios, and for most of the characteristic portfolios constructed in Fama and French (2015). Besides the predictability at the time-series dimension, the factor also contributes to explaining the cross-sectional differences in average returns of industry portfolios. Adding the Forex-specific factor greatly enhances the pricing ability of CAPM or Fama-French three-factor model on the cross-sectional industry portfolios, which is a challenging task as shown in Lewellen et al. (2010). Even the original CAPM model augmented with the Forex-specific factor now performs similarly to the recently proposed Fama and French (2015) five-factor model, with comparable adjusted R^2 41.9% and 42.7% respectively. Notice that the above implications for the stock market is achieved when the Forex-specific factor is required to reconcile the fluctuations of exchange rate. Therefore, the results here strongly support the close connection between the foreign exchange and the stock markets.

There are three main contributions in the present study. First and foremost, our work is similar to Atanasov and Nitschka (2015) in the sense that I both study the common source of systematic risk between those two markets. While they uncover the integration by exploring the effect of discount rate and cash-flow news of stock return on the interest rate sorted currency portfolios, I use data of exchange rate to estimate the pricing kernels within a no-arbitrage affine model and investigate the implications of a key factor (Forex-specific factor) in the estimated pricing kernel on the stock market. Therefore, our work can be treated as a complementary to theirs. Also, their study relies on the ICAPM framework. Thus, they assume that the SDF is a linear function of exogenous risk factors. Instead, I show that the SDF model is an equilibrium outcome, and the risk factor is endogenously estimated from the exchange rate and the interest rate data. In addition to the implications for the aggregate stock market, the present paper also studies the pricing of currency risk in different industry portfolios, similar to Francis et al. (2008). Again, their currency risk factor is exogenously constructed instead of endogenously estimated. Another difference is that I evaluate the impact of risk factor on cross-section industry portfolio returns in a simple unconditional factor model, while they use a conditional model. Although the conditional model has the advantage of incorporating the time-varying investment opportunity set, its empirical implementation and results are possibly sensitive to the selection of conditioning variables.

Second, this paper contributes to the literature on the joint modeling of exchange rate and interest rate (see e.g. Inci and Lu (2004), Anderson et al. (2010)). While previous papers restrict their attention in those two markets, I show that the implication can be extended to other asset markets. Hence I bridge the gap between the literature of term structure and stock return predictability. Also, most previous studies use models whose states are all latent to explain the interest rate and exchange rate, one exception is Yin and Li (2014), who use models with all states being observed. Both approaches have shortcomings. On the one hand, the latent factors have trouble mapping directly to macroeconomic interpretations. On the other hand, since exchange rate is far more volatile than many macroeconomic quantities, the model with all macro states may result in bad fit. In this paper, I combine those two approaches by working with a model where most states are all observables, but I introduce one latent state to account for the volatile exchange rate. I show that the estimated model can replicate almost perfectly the movement of exchange rate return, yet retain the satisfactory yield curve fit by the classical affine term structure model. The model performance is remarkable since Sarno et al. (2012) indicates that for many models there is a substantial trade-off between the accuracy of yield curve fitting and exchange rate return.

Third, this article extends the discussions in Corradi et al. (2013) to the foreign exchange market by studying how exchange rate volatility and implied volatility changes in response to macroeconomic states in an internally consistent no-arbitrage model. The literature on the determinants of exchange rate volatility such as Devereux and Lane (2003) mainly uses the regression approach together with regressors motivated by the economic theory. Instead, I adopt an asset pricing approach, and relate the exchange rate to the pricing kernels in a no-arbitrage manner. In addition, I also discuss the driving forces of currency option implied volatility.

4.2 Model

The model is a two-country extension of the macro-factor term structure model in Ang and Piazzesi (2003) and Joslin et al. (2014), where the home and foreign country are U.S. and U.K. respectively. Such model has been shown by numerous literature to be capable of well capturing the bond yield. To take into account the exchange rate data, in addition to observable states for each country, I add one latent state (Forex-specific factor) that only affects the exchange rate but not bond yield, neither in the spanned nor unspanned way. This way of modeling provides the flexibility of fitting the data since exchange rate return is far more volatile than bond yield.[2]

4.2.1 State Dynamics

I include two kinds of observable states into the model. First, since it has been widely accepted that yield curves can be well characterized by a small number of factors, I use portfolios of bond yields, i.e. the first two principal components of the yield curve, as one class of observables. Those two states have clear interpretations as the level and slope factor, and they account for around 99% of cross sectional bond yield variations in the sample studied here. Adding higher order principal factors contributes little to the model fit, whereas the number of parameters will explode.

In addition, I include inflation and industrial production growth into the observable states. There are two reasons to consider those factors. First, mounting evidence documents the existence of unspanned risk in bond market (see e.g. Duffee

[2]See Anderson et al. (2010) for a similar modeling strategy.

(2011)). That is, the bond risk premia can't be well explained by the cross-section of yields, but can be explained by variables that do not contribute to the cross-section fit of yield curve. Joslin et al. (2014) find that the measures of inflation and growth have large effects on bond risk premia, and thus shall be good candidate for unspanned risk factors. Second, the effects of those two states for exchange rate have been well studied in the literature (see e.g. Engel (2014) for a recent review). A number of theoretical models find that inflation and economic growth can be quite relevant for understanding the fluctuations of nominal exchange rate, thus it will be interesting to investigate the empirical performance of such states in tracking the exchange rate movements.

The observable states in two countries are highly correlated with each other, with correlations ranging from 0.5 to 0.99. To facilitate the interpretation of each state, I follow Jotikasthira et al. (2015) by projecting the foreign variables on the associated U.S. variables, and taking the residual as the foreign country specific states. This projection is also consistent with the literature of international transmission of shocks, which mainly finds that the U.S. market has dominant role in driving global financial market.[3]

For home country, denote 4×1 observable macro states as $X_t = [P_t', M_t']'$ and the Forex-specific factor as x_t, where P_t includes the first two principal components of bond yield curve and M_t includes the measures of inflation and growth. I assume that X_t and x_t follow the process:

$$X_{t+1} = \mu_o + \psi_o X_t + \Sigma_o \eta_{t+1}, \tag{4.2.1}$$

$$x_{t+1} = \mu_x + \phi_x x_t + \sigma_x \nu_{t+1}, \tag{4.2.2}$$

where μ_0 is 4×1, ψ_o and Σ_o are 4×4 matrices, μ_x, ϕ_x, σ_x are all scalars. For foreign country, the definitions of states are similar but with superscript *. The dynamics of

[3] See e.g. Ehrmann et al. (2011).

those states are assumed to follow:

$$X^*_{t+1} = \mu^*_o + \psi^*_{oh} X_t + \psi^*_{of} X^*_t + \Sigma^*_{oh}\eta_{t+1} + \Sigma^*_{of}\eta^*_{t+1}, \tag{4.2.3}$$

$$x_{t+1} = \mu_x + \phi_x x_t + \sigma_x \nu_{t+1}, \tag{4.2.4}$$

where μ^*_o is 4×1, ψ^*_{oh}, ψ^*_{of}, Σ^*_{oh} and Σ^*_{of} are 4×4 matrices. Above dynamics actually assume that the home country states affect the foreign states, whereas the opposite transmission is not allowed. Also, the common Forex-specific factor is assumed not to affect the observable states of both countries. As mentioned before, the existence of such component is crucial for fitting the exchange rate data, and can be motivated as common long-run growth component in the equilibrium model of Colacito and Croce (2011).

4.2.2 Pricing kernel

Denote $Z_t = [X_t, X^*_t, x_t]$ as the collection of all states of two countries. According to assumptions in the previous subsection, the dynamics of Z_t can be written as:

$$Z_{t+1} = \mu + \Phi Z_t + \Sigma\varepsilon_{t+1}, \tag{4.2.5}$$

where $\mu = \begin{bmatrix} \mu_0 \\ \mu^*_0 \\ \mu_x \end{bmatrix}, \Phi = \begin{bmatrix} \psi_0 & 0 & 0 \\ \psi^*_{0h} & \psi^*_{0f} & 0 \\ 0 & 0 & \phi_x \end{bmatrix}, \Sigma = \begin{bmatrix} \Sigma_o & 0 & 0 \\ \Sigma^*_{0h} & \Sigma^*_{0f} & 0 \\ 0 & 0 & \sigma_x \end{bmatrix}, \varepsilon_t = \begin{bmatrix} \eta_t \\ \eta^*_t \\ \nu_t \end{bmatrix}$.

Assume that the log domestic economy-wide nominal pricing kernel is given by:

$$m_{t+1} = -r_t - \frac{1}{2}\lambda'_t\lambda_t - \lambda'_t\varepsilon_{t+1}, \tag{4.2.6}$$

where r_t is the domestic short rate, λ_t consists of the time-varying prices of risk. Following the literature of affine term structure, λ_t is assumed to be affine in states:

$$\lambda_t = \lambda_0 + \lambda_1 Z_t, \tag{4.2.7}$$

where λ_0 is 9×1, and λ_1 is 9×9 matrix. To be consistent with the orthogonality of Forex-specific factor, the off-diagonal elements of λ_1 that correspond to it are assumed to be zero. Combining this assumption with the physical dynamics of Z_t, equation (4.2.6) can be written as:

$$m_{t+1} = m^B_{t+1} - \frac{1}{2}\lambda^2_{xt} - \lambda_{xt}\nu_{t+1}, \tag{4.2.8}$$

where m^B_{t+1} is the bond-specific pricing kernel, $\lambda_{xt} = \lambda_{0x} + \lambda_{1x}x_t$ is the risk price of Forex-specific factor.

4.2.3 Restrictions on risk premia parameters

The price of risk λ_t is determined by state vector $Z_t = [P'_t, M'_t, P^{*'}_t, M^{*'}_t, x_t]'$ as well as the risk premia parameters λ_0 and λ_1, which contain a large number of free parameters. To avoid the over fitting, I therefore impose several restrictions on λ_0 and λ_1 of both countries.

To facilitate the presentation, $\lambda_0, \lambda_1, \lambda^*_0, \lambda^*_1$ are written in the following block form:

$$\lambda_0 = \begin{bmatrix} \lambda_{0P} \\ \lambda_{0M} \\ \lambda_{0P^*} \\ \lambda_{0M^*} \\ \lambda_{0x} \end{bmatrix}, \lambda_1 = \begin{bmatrix} \lambda_{PP} & \lambda_{PM} & \lambda_{PP^*} & \lambda_{PM^*} & \lambda_{Px} \\ \lambda_{MP} & \lambda_{MM} & \lambda_{MP^*} & \lambda_{MM^*} & \lambda_{Mx} \\ \lambda_{P^*P} & \lambda_{P^*M} & \lambda_{P^*P^*} & \lambda_{P^*M^*} & \lambda_{P^*x} \\ \lambda_{M^*P} & \lambda_{M^*M} & \lambda_{M^*P^*} & \lambda_{M^*M^*} & \lambda_{M^*x} \\ \lambda_{xP} & \lambda_{xM} & \lambda_{xP^*} & \lambda_{xM^*} & \lambda_{xx} \end{bmatrix},$$

$$\lambda^*_0 = \begin{bmatrix} \lambda^*_{0P} \\ \lambda^*_{0M} \\ \lambda^*_{0P^*} \\ \lambda^*_{0M^*} \\ \lambda^*_{0x} \end{bmatrix}, \lambda^*_1 = \begin{bmatrix} \lambda^*_{PP} & \lambda^*_{PM} & \lambda^*_{PP^*} & \lambda^*_{PM^*} & \lambda^*_{Px} \\ \lambda^*_{MP} & \lambda^*_{MM} & \lambda^*_{MP^*} & \lambda^*_{MM^*} & \lambda^*_{Mx} \\ \lambda^*_{P^*P} & \lambda^*_{P^*M} & \lambda^*_{P^*P^*} & \lambda^*_{P^*M^*} & \lambda^*_{P^*x} \\ \lambda^*_{M^*P} & \lambda^*_{M^*M} & \lambda^*_{M^*P^*} & \lambda^*_{M^*M^*} & \lambda^*_{M^*x} \\ \lambda^*_{xP} & \lambda^*_{xM} & \lambda^*_{xP^*} & \lambda^*_{xM^*} & \lambda^*_{xx} \end{bmatrix}.$$

The restrictions are made based on some evidence in the empirical literature. For home country investor, consistent with (4.2.1), I assume that there are no risk compensations for the foreign states. This exploits the empirical facts (see e.g. Eun and Shim (1989)) that the shocks from U.S. financial market have large impact on other markets, but not vice versa. The same empirical pattern also provides guidance on restricting the price of risk for foreign country, that is, the parameters in λ_1^* remain unrestricted to reflect such transmission of shocks. In terms of λ_0 and λ_0^*, I restrict $\lambda_{0P^*}, \lambda_{0M^*}, \lambda_{0P}^*, \lambda_{0M}^*$ to be zero. Since λ_0 characterizes the long run mean of bond yield, this assumption simply claims that the long run mean of one country's bond yield is only determined by its country-specific parameters.[4]

4.2.4 Bond Prices

Following the literature, I assume that the one-period short rate of home country is an affine function of the home level and slope factors, that is,

$$r_t = \delta_0 + \delta_1' P_t. \tag{4.2.9}$$

Then the bond yield with maturity n periods ahead admits an affine form:

$$y_t = a_n + b_n' P_t, \tag{4.2.10}$$

where $a_n = -\frac{A_n}{n}, b_n = -\frac{B_n}{n}$, A_n and B_n follow the recursions:

$$A_n = A_{n-1} + B_{n-1}'(\mu_p - \Sigma_P \lambda_{0P}) \frac{1}{2} B_{n-1}' \Sigma_P \Sigma_P' B_{n-1} + A_1, \tag{4.2.11}$$

$$B_n' = B_{n-1}'(\Phi_p - \Sigma_P \lambda_{1P}) + B_1', \tag{4.2.12}$$

where μ_P, Σ_P, Φ_P are sub-matrix of μ, Φ, Σ in (4.2.5), and $\lambda_{0P}, \lambda_{1P}$ are sub-matrix of λ_0, λ_1 in (4.2.7) that correspond to pricing factors P_t. The derivation of foreign

[4] After applying those restrictions, $\lambda_{0P^*}, \lambda_{0M^*}, \lambda_{PP^*}, \lambda_{PM^*}, \lambda_{MP^*}, \lambda_{MM^*}, \lambda_{xP}, \lambda_{xM}, \lambda_{Px}, \lambda_{Mx}, \lambda_{xP^*}, \lambda_{xM^*}$ will be blocks of zero.

bond prices is similar and thus omitted here.

4.2.5 Exchange rate and implied variance

I assume that both home and foreign markets are complete, then the log nominal exchange rate return is the difference between log SDF (see Backus et al. (2001)) :

$$\Delta s_{t+1} = m^*_{t+1} - m_{t+1} = (r_t - r^*_t) + \frac{1}{2}(\lambda_t^{'}\lambda_t - \lambda_t^{*'}\lambda_t^{*'}) + (\lambda_t - \lambda_t^*)^{'}\varepsilon_{t+1}. \quad (4.2.13)$$

In this paper, I also explore the implications for currency option implied volatility. Previous literature of affine term structure model only focuses on the level of bond yield or exchange rate return, nonetheless, the model also has testable implications for the implied volatility. In particular, a closed form expression for the risk neutral one-period ahead expectation of conditional variance $E_t^Q[\sigma^2_{t+1}]$ can be obtained in this model. Formally:

PROPOSITION 3. *When markets of home and foreign country are both complete, and the log stochastic discount factor for each country is given in the form of (4.2.6). Denote $a = \lambda_0 - \lambda_0^*$, $b = \lambda_1 - \lambda_1^*$, then the risk neutral expectation of one-period ahead conditional variance of exchange rate return is:*

$$\begin{aligned} E_t^Q[\sigma^2_{t+1}] &= tr(b'\Sigma\Sigma'b + b'\Sigma\lambda_t\lambda_t^{'}\Sigma'b) - 2((a + b'(\mu + \Phi Z_t))'b'\Sigma\lambda_t) + \\ &\quad (a + b'(\mu + \Phi Z_t))'(a + b'(\mu + \Phi Z_t)). \end{aligned} \quad (4.2.14)$$

In later sections, I include the data of currency implied variance in the model estimation. As suggested by Graveline (2006), the option implied volatility provides useful information about the exchange rate volatility that is much harder to identify from the time-series data on exchange rate.

4.2.6 Complete market and exchange rates

Before proceeding to the solution method of the model, it's worthwhile to discuss an important aspect of the model setting. As pointed out by Backus et al. (2001), equation (4.2.13) is the sufficient and necessary condition for the determination of exchange rate when no arbitrage holds and markets in both countries are complete (such that the comprehensive stochastic discount factor in both countries are unique). However, in most affine term structure models, the SDF is identified through bond prices. This identification though provides good fit of bond yield curve, by construction it has difficulty in accounting for exchange rate data since volatility of exchange rate return is much higher than that of interest rate. Therefore, equation (4.2.13) is easily rejected by the data. Previous studies then try different ways to deal with the term structure and exchange rate in a unifying framework. One of an early example is in Brandt and Santa-Clara (2002), where they abandon the complete market setting and use an exogenous process o_t to bridge the gap between exchange rate and ratio of SDF (by setting $\Delta s_t = m_t^* - m_t + o_t$). Nonetheless, this procedure is ad hoc and more importantly, equation (4.2.13) now becomes necessary but not sufficient condition for exchange rate determination. This will create a theoretical drawback for the determination of exchange rate.

In contrast, the assumption of complete market setting is preserved in this model. Notice that the relation (4.2.13) shall hold with the comprehensive stochastic discount factor that price all asset payoffs, it's then feasible to construct pricing kernel such that a part of it is used to pricing bonds, while the rest can only be identified through other asset classes such as exchange rate.[5] This motivates the use of Forex-specific factor, not directly on the exchange rate relation (4.2.13) as in Brandt and Santa-Clara (2002), but as the state of SDF. The orthogonality of such factor with respect to bond states gives the model flexibility of fitting exchange rate data, while not deteriorating its bond pricing performance.

[5] See a similar argument in Joslin et al. (2014).

4.3 Data and Econometric Methodology

4.3.1 Data

I sample the data at monthly frequency from 1996M5-2016M2. I download U.S. nominal bond yields from Fed H.15 release, and U.K. nominal bond yields from the Bank of England. I consider the maturities with 0.25, 0.5, 1, 2, 3, 5, 7, 10 years for U.S. and 1, 2, 3, 5, 7, 10 years for U.K.. I take one-month interbank rate as a proxy for short rate, and the data is downloaded from Global Financial Database.

For macroeconomic states, year over year (YOY) industrial production growth and CPI growth are treated as proxies for economic growth and inflation respectively. The exchange rate return is the log growth of spot exchange rate. Implied variance is calculated from at-the-money one month European currency options as in Londono and Zhou (2014). The data is obtained from Bloomberg.

The interest rate and implied variance data are denominated in the annual frequency, I transform them to the monthly frequency by dividing 12. For daily data, I use the data on the last trading day of each month to form the monthly sample.

4.3.2 Solution method

The model to be estimated consists of the following measurement equations:

$$y_t^n = a_n + b_n^{'} P_t + \zeta_{1t}, \quad (4.3.1a)$$

$$y_t^{*n} = a_n^* + b_n^{*'} P_t^* + \zeta_{2t}, \quad (4.3.1b)$$

$$\begin{aligned} \Delta s_t = {} & (y_{t-1}^1 - y_{t-1}^{*1}) + \frac{1}{2}(\lambda_{t-1}^{'} \lambda_{t-1} - \lambda_{t-1}^{*'} \lambda_{t-1}^*) \\ & + (\lambda_{t-1}' - \lambda_{t-1}^{*'}) \Sigma^{-1} (X_t - \mu - \Phi X_{t-1}) + \zeta_{3t}, \quad (4.3.1c) \end{aligned}$$

$$\begin{aligned} E_t^Q[\sigma_{t+1}^2] = {} & tr(b'\Sigma\Sigma' b + b'\Sigma\lambda_t \lambda_t^{'} \Sigma' b) - 2((a + b'(\mu + \Phi X_t))' b' \Sigma \lambda_t) \\ & + (a + b'(\mu + \Phi X_t))'(a + b'(\mu + \Phi X_t)) + \zeta_{4t}, \quad (4.3.1d) \end{aligned}$$

where ζ_{1t}, ζ_{2t}, ζ_{3t} and ζ_{4t} are measurement errors of the data.The first two equations are the equations for the bond yields, and the rest are the equations for the exchange rate determination and currency implied variance. The Forex-specific factor dynamics is the state transition equation:

$$x_{t+1} = \mu_x + \phi_x x_t + \sigma_x \varepsilon_{t+1}. \tag{4.3.2}$$

System (4.3.1)-(4.3.2) constitutes a nonlinear state space model and can be estimated via maximum likelihood. However, empirically estimating such a model is challenging for two reasons. First, the number of parameters is large. Second, the likelihood based estimation calls for unscented kalman filtering or particle filtering. Whether those methods can perform well for the parameter estimation, especially when the number of parameters is so large, is questionable. Consequently, I use a feasible two-stage estimation scheme by exploiting the orthogonal structure of Forex-specific factor with respect to bond pricing.[6] In the first stage, I estimate the affine term structure model using macro and bond data. Then in the second stage, I estimate a nonlinear state space formed by equations of exchange rate determination and option implied variance, by fixing the point estimates obtained from the first step. More specifically, at the first stage, I consider the following linear Gaussian state space model:

$$y_t^n = a_n + b_n^{'} P_t + \zeta_{1t}, \tag{4.3.3a}$$

$$y_t^{*n} = a_n^* + b_n^{*'} P_t^* + \zeta_{2t}, \tag{4.3.3b}$$

$$V_t = X_t + \zeta_{1t}^V, \tag{4.3.3c}$$

$$V_t^* = X_t^* + \zeta_{2t}^V, \tag{4.3.3d}$$

$$X_t = \mu + \Phi X_{t-1} + \Sigma \varepsilon_t, \tag{4.3.3e}$$

$$X_t^* = \mu^* + \Phi^* X_{t-1}^* + \Sigma^* \varepsilon_t^*, \tag{4.3.3f}$$

[6]Similar multi-step estimation strategy can be found in Baele et al. (2010) and Corradi et al. (2013).

where measurement equations are (4.3.3a)-(4.3.3d), and state equations are formed by (4.3.3e)-(4.3.3f). The measurement errors are assumed as: $\zeta_{1t} \sim N(0, \sigma_h^2)$, $\zeta_{2t} \sim N(0, \sigma_f^2)$, $\zeta_{1t}^V \sim N(0, \sigma_m^2)$, $\zeta_{2t}^V \sim N(0, \sigma_m^2)$. In other words, bond yields and macroeconomic states in both countries are observed with errors. The standard deviations for measurement errors of domestic and foreign bond yields are identical within each country but different across countries, while the measurement errors for macroeconomic states of both countries follow exactly the same distribution.

System (4.3.3) can be estimated using maximum likelihood, where likelihood is evaluated via Kalman filtering. The number of parameters at this stage is still quite large, thus a good starting value is needed. I use a linear estimator proposed by de Los Rios (2015) as the starting value for optimization. The advantage of such method lies in its simplicity and robustness, as well as delivering sensible parameters that help fit the data.

In the second step, I estimate the following nonlinear state space model:

$$\Delta s_t = (y_{t-1}^1 - y_{t-1}^{*1}) + \frac{1}{2}(\lambda_{t-1}^{'}\lambda_{t-1} - \lambda_{t-1}^{*'}\lambda_{t-1}^{*}) + (\lambda_{t-1}^{'} - \lambda_{t-1}^{*'})\Sigma^{-1} (X_t - \mu - \Phi X_{t-1}) + \eta_{3t}, \quad (4.3.4a)$$

$$E_t^Q[\sigma_{t+1}^2] = tr(b'\Sigma\Sigma' b + b'\Sigma\lambda_t\lambda_t^{'}\Sigma' b) - 2((a + b'(\mu + \Phi X_t))' b'\Sigma\lambda_t) + (a + b'(\mu + \Phi X_t))'(a + b'(\mu + \Phi X_t)) + \eta_{4t}, \quad (4.3.4b)$$

$$x_t = \mu_x + \phi_x x_{t-1} + \sigma_x \varepsilon_t, \quad (4.3.4c)$$

where (4.3.4a)-(4.3.4b) are measurement equations, and (4.3.4c) is the state equation. Here the error terms η_{3t} and η_{4t} follow scaled t-distribution with scales σ_3, σ_4 and degree of freedom v_3, v_4 respectively. Jacquier et al. (2004) show that the model with t-distribution error term is more flexible in dealing with outliers. Due to the extreme observations during the period of financial turmoil in 2008, t-distributed measurement error is more suitable than standard normal distribution in this context. Moreover, I impose the restriction on σ_3 and σ_4 such that the model explains most of variations in the data, and the measurement error can account up to 10% of total fluctuations.[7]

The number of parameters at this stage is medium and manageable. I estimate the parameters and the latent state in this system jointly using auxiliary particle filtering, which is quite popular in estimating the parameters of nonlinear state space. [8] For the initial values of optimization, I consider many sets of initial parameters, which are drawn randomly from a reasonable domain, then I run maximum likelihood and only keep the estimates with the largest likelihood in the end.

At this stage, it is worthwhile pointing out the econometric role played by the measurement equation of implied variance (4.3.4b). Since in the second step estimation, only exchange rate related quantities are used, and notice that the Forex-specific factor is assumed to reconcile the fluctuations of exchange rate return, with no impact on bond pricing. Thus the model is exactly-identified if I ignore (4.3.4b), and the model may potentially fit the data arbitrarily well (even though (4.3.4a) is a highly nonlinear function of Forex-specific factor). After introducing (4.3.4b) as one additional measurement equation, the system is now over-identified and the model fit is not perfect ex ante.

4.4 Estimation Results

4.4.1 Results of the first-stage estimation

Table 4.1 displays the VAR estimation results of observable states for both countries as well as the common Forex-specific factor. The estimates of the diagonal of Φ show that all macro and Forex-specific states are persistent. For diagonals of Σ, consistent with the intuition, the Forex-specific factor, which is designed to describe the foreign exchange market, is far more volatile than other macro states. While most of the parameters on the off-diagonal of Φ are statistically insignificant, one can still obtain several interesting economic observations. First, the slope factor

[7] This assumption is also made during the model estimation in Schmitt-Grohé and Uribe (2012).

[8] In Appendix D, I discuss the accuracy of the particle filter in estimating the latent state.

predicts positively almost all other states in either home or foreign country. This is consistent with previous literature documenting the strong (positive) predictive ability of yield curve slope on future economic activity (see e.g. Estrella (2005)). Second, the yield curve level predicts higher inflation in both countries. As shown by Diebold et al. (2006), the yield curve level factor can be treated as the bond market perception of long run inflation. In terms of cross-country transmission, an interesting pattern is that the increase of U.S. level triggers negative response of all U.K. states. Such an effect can be reconciled with the literature on international transmission of shocks. For example, Mumtaz and Surico (2009) find that U.K. inflation positively respond to lower interest rate of other industrialized countries in a factor-augmented VAR framework. Given the dominant role of U.S. among the industrialized countries, it's then natural to have higher interest rate, slope, inflation and growth for U.K. after a negative innovation in U.S. interest rate.

Table 4.1. VAR estimation

The table reports the estimation results of model (4.2.5): $Z_{t+1} = \mu + \Phi Z_t + \Sigma\varepsilon_{t+1}$, where Z_t=[U.S. Level, U.S. Slope, U.S. Inflation, U.S. Growth, U.K. Level, U.K. Slope, U.K. Inflation, U.K. Growth, Forex-specific]. The empty cells in the table represent zero restrictions. Robust standard errors of White (1982) are reported in the parentheses. *, ** and *** indicate significance at the 10%, 5%, and 1% levels.

$\mu(\times 10^3)$	Φ									$\Sigma(\times 10^3)$								
0.170	0.993	-0.011	-0.065	0.016						0.473	0.145	0.053	0.044					
(0.223)	(0.001)***	(0.060)	(0.053)	(0.020)						(0.034)***	(0.058)**	(0.018)***	(0.045)					
0.242	0.002	0.912	-0.011	-0.015						0.144	0.232	0.033	-0.004					
(0.041)***	(0.002)	(0.001)***	(0.032)	(0.013)						(0.017)***	(0.013)***	(0.013)**	(0.028)					
0.071	0.005	0.013	0.918	0.015						0.053	0.034	0.357	0.040					
(0.124)	(0.007)	(0.035)	(0.031)***	(0.013)						(0.041)	(0.032)	(0.022)***	(0.045)					
-0.469	0.005	0.231	-0.104	0.966						0.044	-0.004	0.040	0.782					
(0.399)	(0.016)	(0.113)**	(0.098)	(0.024)***						(0.071)	(0.051)	(0.112)	(0.069)***					
0.010	-0.006	0.021	0.018	-0.007	0.988	0.012	-0.062	0.020		-0.474	-0.143	-0.053	-0.045	0.399	0.072	0.030	0.028	
(0.303)	(0.011)	(0.057)	(0.074)	(0.038)	(0.001)***	(0.007)	(0.031)**	(0.051)		(0.341)	(0.181)	(0.091)	(0.045)	(0.215)*	(0.092)	(0.195)	(0.108)	
-0.069	-0.003	0.017	0.016	0.008	-0.001	0.934	0.010	-0.010		-0.110	-0.178	-0.026	0.003	0.072	0.158	-0.003	-0.123	
(0.053)	(0.008)	(0.016)	(0.075)	(0.028)	(0.007)	(0.032)***	(0.020)	(0.020)		(0.029)***	(0.053)***	(0.125)	(0.019)	(0.055)	(0.047)***	(0.021)	(0.050)**	
-0.049	-0.003	0.001	0.047	-0.009	0.001	0.015	0.967	0.008		-0.039	-0.025	-0.267	-0.030	0.029	-0.003	0.224	0.109	
(0.164)	(0.012)	(0.031)	(0.049)	(0.019)	(0.024)	(0.075)	(0.051)***	(0.041)		(0.072)	(0.063)	(0.173)	(0.059)	(0.056)	(0.199)	(0.162)	(0.248)	
0.172	-0.002	0.008	-0.091	-0.046	-0.001	0.152	-0.179	0.860		-0.019	0.002	-0.017	-0.317	0.028	-0.123	0.109	1.099	
(0.554)	(0.036)	(0.110)	(0.267)	(0.056)	(0.045)	(0.172)	(0.130)	(0.085)***		(0.373)	(0.417)	(0.704)	(0.097)***	(0.468)	(0.231)	(0.441)	(0.339)***	
2.12									0.819									6.292
(9.40)									(0.047)***									(0.700)***

Turning to the price of risk, Table 4.2 shows the estimation result. The risk loadings for each country's level and slope risk are similar. On the one hand, level risk is negatively affected by the level and slope factor, although the loadings are not significant for U.S. investor. On the other hand, the time-varying slope risk is negatively driven by the slope factor itself. This stems from the fact that a higher yield curve slope predicts the economic boom, during which the risk premia will be low.

When it comes to the parameters of risk price for inflation and growth, it's clear that their magnitudes are much higher than those of bond pricing factors. This is not surprising given the fact that those parameters are identified from exchange rate, which is much volatile than bond yields,[9]. For inflation risk, higher inflation and economic growth will induce higher inflation risk premium in home country, while the effect in foreign country is opposite. This is consistent with a comparative study of U.S. and Euro area by Hördahl and Tristani (2010), in which they find that the inflation risk premium is lower when output gap is increasing for Euro area, but such relation is opposite for U.S.. The former is in line with the common wisdom of countercyclical risk premium, while the latter effect can emerge since there will be higher risk of inflation surprises at economic boom. Whether one state moves up or down the inflation risk premium depends on the relative magnitude of those two effects. This mechanism also explains why inflation risk premium of foreign country is positively and significantly driven by both country's slope factor: a better prospect of economy can still increase the inflation risk premium when the latter effect dominates. For fluctuations in growth risk premium, the growth factor itself has the largest and significant effect for U.S., while the estimates for U.K. are insignificant. The opposite impact of economic growth factor on growth risk premium for two countries can be understood in analogy to the inflation risk premium.

The above discussions indicate that those two economies have heterogeneous re-

[9]In classical affine term structure such as Joslin et al. (2014) those parameters can't be identified solely from the bond market. They also propose the possible identification from other asset markets.

sponses to macro states. However, they have similar exposure to the Forex-specific factor. Time-varying risk compensation for Forex-specific factor is almost identical, with highly significant estimates. This justifies our assumption about its commonality between two countries, and also suggests that such factor may potentially capture some systematic risk.

Table 4.2. Risk premia parameters

The table reports the estimates of risk premia parameters. The four rows of λ_0 and four columns of λ_1 represent the parameters corresponding to U.S. Level, U.S. Slope, U.S. Inflation and U.S. Growth. The four rows of λ_0^* represent the parameters for U.K. Level, U.K. Slope, U.K. Inflation and U.K. Growth, and eight columns of λ_1^* represents those for U.S. Level, U.S. Slope, U.S. Inflation, U.S. Growth, U.K. Level, U.K. Slope, U.K. Inflation and U.K. Growth. $\lambda_{0x}, \lambda_{1x}, \lambda_{0x}^*, \lambda_{1x}^*$ are the risk parameters for the Forex-specific factor. Robust standard errors are reported in the parentheses. *, ** and *** indicate significance at the 10%, 5%, and 1% levels.

Panel A: U.S.								
$\lambda_0(\times 10^3)$			λ_1					
0.256		-0.001	-0.103	-0.065	0.016			
(0.009)		(0.002)	(0.060)*	(0.053)	(0.020)			
0.160		0.005	-0.060	-0.011	-0.015			
(0.011)***		(0.002)**	(0.002)***	(0.032)	(0.013)			
-0.158		0.645	-0.603	1.612	0.753			
(10.80)		(1.314)	(1.400)	(4.985)	(1.146)			
0.189		0.087	0.608	0.533	-2.164			
(3.10)		(0.507)	(1.299)	(1.144)	(0.331)***			
$\lambda_{0x}(\times 10^3)$			λ_{1x}					
-1.060			-1.199					
(19.60)			(0.008)***					
Panel B: U.K.								
$\lambda_0^*(\times 10^3)$				λ_1^*				
0.222	-0.003	-0.053	-0.047	0.008	-0.003	-0.070	-0.062	0.020
(0.006)***	(0.001)***	(0.005)***	(0.024)*	(0.021)	(0.001)***	(0.007)***	(0.031)**	(0.051)
0.079	-0.001	-0.039	0.007	-0.004	-0.001	-0.052	0.010	-0.010
(0.012)	(0.007)	(0.024)	(0.015)	(0.009)	(0.007)	(0.032)	(0.020)	(0.020)
-2.160	-0.874	5.246	-0.614	-0.248	-0.873	6.920	-0.820	-0.597
(2.500)	(0.783)	(0.802)***	(1.873)	(0.932)	(0.782)	(1.057)***	(2.503)	(2.238)
2.673	-0.320	1.416	-0.062	0.678	-0.319	1.868	-0.083	1.627
(2.200)	(0.899)	(1.156)	(0.655)	(0.373)*	(0.897)	(1.525)	(0.875)	(0.895)*
$\lambda_{0x}(\times 10^3)$				λ_{1x}				
4.500				-1.065				
(37.00)				(0.003)***				

Though the focus of this paper is the fit of exchange rate data, the result can be misleading if the fit for bond worsens substantially, given the tight relation of cross-country SDF in equation (4.2.13). Thus I report the performance of yield curve fitting in Table 4.3. As can be seen from the table, the pricing errors are around 10 basis points (annualized) for all maturities. The magnitudes are small and comparable with studies that focus only on yield curve fitting (see e.g. Piazzesi (2005)), suggesting that the model has satisfactory description of bond yield data.

Table 4.3. Yield curve fitting

The table reports bond pricing errors and standard deviations of measurement errors. The pricing errors are calculated as the RMSE between the model implied yields and the data.

Panel A: U.S.								
Maturity (year)	0.25	0.5	1	2	3	5	7	10
Pricing errors (annualized bps)	13	7	7	12	11	7	7	13
Measuring Errors (annualized bps)	10							
Panel B: U.K.								
Maturity (year)	1	2	3	5	7	10		
Pricing errors (annulized bps)	11	5	9	7	4	11		
Measuring Errors (annualized bps)	8							

4.4.2 Fit of option implied variance

In this subsection, I discuss the model fit for currency option implied variance. In the data, the mean and standard deviation of the (monthly) implied variance of one-month at-the-money option is 0.07% and 0.06%, while the model generated data has mean 0.06% and standard deviation 0.02%. The measurement error with t-distribution has an estimated degree of freedom 4.22, therefore indicating the fat-tail property in the option data.

The less volatile model-generated quantity is due to the asset volatility spike during 2008 financial crisis, when the macroeconomic factors do not display such dramatic movements. Indeed, I show that after excluding the data points from 2007M12 to 2009M6, the standard deviation for the data and model is now 0.02% and 0.01% respectively. The distance between those two becomes much smaller compared to that obtained from the full sample. Interestingly, the data points during the period of financial turmoil will push up the volatility of data by 3 folds (from 0.02% to 0.06%), while the prediction from the model also doubles. Thus macroeconomic fundamentals and implied volatility can display (conditional) co-movement, instead of little connections as documented by Mixon (2002).

To formally evaluate the fit, I regress the data on the model-implied counterpart to better see the relation between those two quantities, the regression results are:

$$E_t^{\mathbb{Q}}(\sigma_{t+1}^2) = \underset{(-7.05)}{-0.0006} + \underset{(16.01)}{2.045}\hat{E}_t^{\mathbb{Q}}(\sigma_{t+1}^2) + e_t, \qquad R^2 = 52.3\%.$$

The coefficient on $\hat{E}_t^{\mathbb{Q}}(\sigma_{t+1}^2)$ is 2.05, which is significant with a t-statistic 16.01. The deviation from unity regression coefficient is consistent with the above moment comparisons of data and model. Also from the R^2 of the regression, a substantial proportion of variations in the data can be explained by the model. The results thus suggest that the macro-factor affine model, in addition to providing good fit for bond yield, also has the potential to track the movements of currency option implied variance.

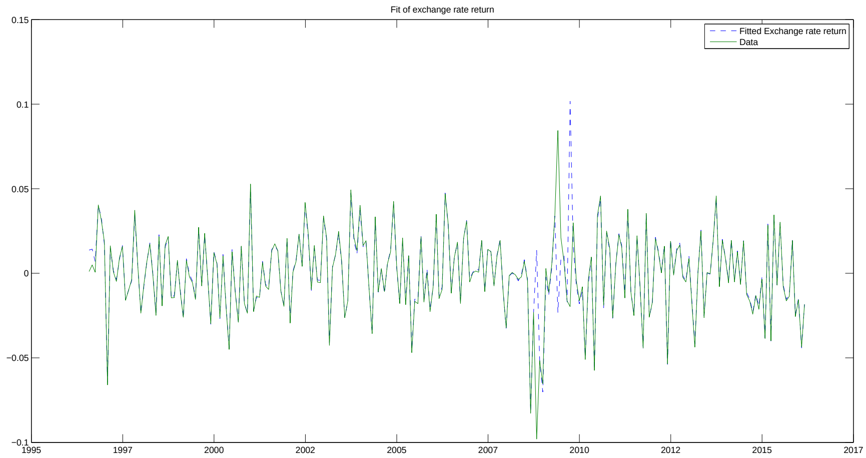
4.4.3 Fit of exchange rate return

Figure 4.1 displays the fit of exchange rate return. The model implied quantity tracks the data quite well, with the correlation coefficient of 0.81. In particular, the model fit is almost perfect except the periods of financial crisis. Recent papers including Brunnermeier et al. (2009) and Adrian et al. (2015) find that extreme exchange rate movements may be related to the funding liquidity. Since the macro states considered in this paper do not include any liquidity-related measures, the bad fit during the crisis may partially be attributed to omitted state variables.

To shed more lights on the underlying drivers of the model fit and the importance of the Forex-specific factor, I implement an exercise similar to variance decomposition. Formally, I calculate the volatility of the return data and the model-implied

Figure 4.1. Fit of exchange rate return

The figure plots the data and the model implied exchange rate return.



return based on the measure proposed in Corradi et al. (2013):

$$Vol_t = \sqrt{6\pi}\frac{1}{12}\sum_{i=1}^{12}|r_{t+1-i}|. \tag{4.4.1}$$

Then I fix the Forex-specific factor at its unconditional mean, and repeat the volatility calculations again. The difference between those two series of volatilities provides a measure of the importance of Forex-specific factor for fitting the data. Similarly, to clarify the role of other macroeconomic states, I present the root-mean-square error (RMSE) between data and model implications when I shut off each macro state once at a time. The decomposition result is shown in Figure 4.2 and the RMSE measures are presented in Table 4.4.

Obviously, a single Forex-specific state can explain a substantial portion of changes in exchange rate volatility. This is not inconsistent with the well-known exchange rate disconnect puzzle stating that the short-term link between exchange rate and economic fundamentals is weak, since the Forex-specific factor is latent and therefore does not map directly to fundamentals. Interestingly, I find that the pure macroeconomic and interest rate factors can still explain some part of the data. In particular, as can be seen from Table 4.4, inflation measures in two countries strongly affect the exchange rate volatility, since the model fit worsens substantial-

Figure 4.2. Variance decomposition of exchange rate return

The figure plots the results of variance decomposition. The dash dot line (Model) represents the model-implied volatility of exchange rate return. The dash line (No Forex-specific) represents the model-implied volatility when the Forex-specific factor is fixed at its unconditional mean. The solid line (Data) is the volatility of the data.

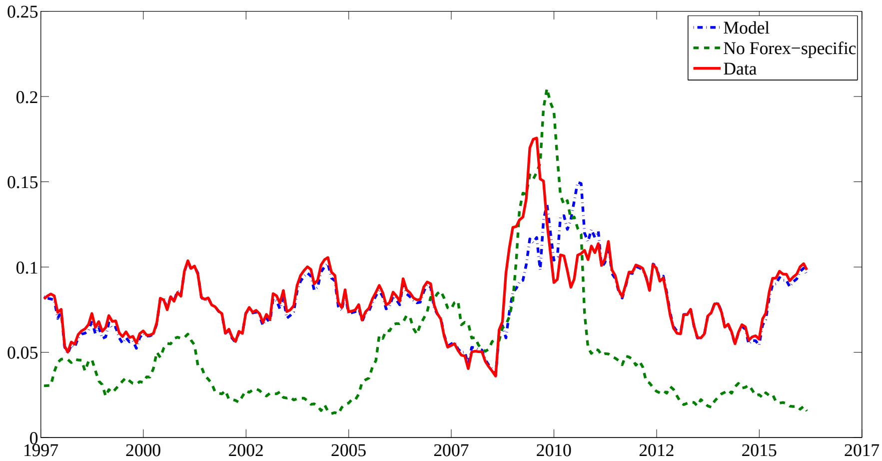


Table 4.4. Loss of Fit

The table reports the loss of fit measures. For each row, I fix one of the states listed in the first column at its unconditional mean, then I calculate the RMSE between the model implied value and the data. The row with state “Benchmark” represents the case when all states are activated.

States	RMSE of return volatility	RMSE of implied variance($\times 10^3$)
Benchmark	0.0131	0.5252
U.S. Level	0.0098	0.5072
U.S. Slope	0.0136	0.5086
U.S. Inflation	0.0231	0.5046
U.S. Growth	0.0111	0.6179
U.K. Level	0.0133	0.5082
U.K. Slope	0.0120	0.5094
U.K. Inflation	0.0277	0.5631
U.K. Growth	0.0131	0.4970
Latent	0.0466	0.5255

ly after omit of the variation of U.S. or U.K. inflations. Many previous empirical studies on the macroeconomic determinants of exchange rate mainly focus on the predictive ability of fundamentals in the regression framework and find quite limited role for the macro factors (see a comprehensive review by Rossi (2013)). In contrast, the successful detection of the close relation between exchange rate and fundamentals in this paper is of interest for two reasons. First, the two-stage estimation scheme does not allow the dynamics of macroeconomic states to reconcile the exchange rate data, therefore the role of macroeconomic states is not a result of manipulation. Also, I implement the bottom up modeling strategy by starting from a reduced form model of stochastic discount factor and the no-arbitrage condition, then the exchange rate is determined from the cross-country difference in log stochastic discount factor, thus exchange rate is connected to the fundamentals in a more rigorous way compared to the regression method.

Another interesting observation arises by comparing last two columns of Table 4.4. Although the Forex-specific factor is quite important for exchange rate return, it contributes almost nothing to the fit of the option implied variance. This suggests that different drivers underlie exchange rate and option market. For currency options, the U.S. growth appears to be the most important state. This is intuitive because U.S. growth characterizes to a large extent the world economy prospects and thus the forward-looking nature of option market will treat it as an important source of risk.[10]

4.5 Implications for Stock Markets

4.5.1 Results of predictive regressions

In this section, I explore the potential role of Forex-specific factor, which according to previous discussions is an important factor entering the log SDF and determining the exchange rate volatility, for the stock markets of U.S. and U.K.. For the simplicity of notations, I denote the value of such factor at time t as FX_t.

Following the literature on stock return predictability (see recent papers e.g. Welch and Goyal (2008), Rapach et al. (2016b)), I study the following predictive regression:

$$r_{t+1} = \alpha + \beta z_t + \varepsilon_{t+1}, \tag{4.5.1}$$

[10]Even though the implied volatility used here is at one month horizon, on which macroeconomic fundamentals may have quite limited impact directly, the strong co-movement of short-term and long-term implied volatility will transmit the macro effect on long-horizon options to short-horizon.

where r_{t+1} is the one-period ahead excess return, and the predictor z_t characterizes the time-varying expected return. I utilize (4.5.1) to test the ability of Forex-specific factor in capturing the time-varying expected return of stock market. For comparison, I also evaluate the performance of other 14 predictors that are commonly used in the literature. Since data of all corresponding predictors in U.K. is not available, I use U.S. predictors to forecast the U.K. stock market. The details of constructing those variables can be found in the Appendix A. Table 4.5 gives the predictability results for the excess returns of aggregate stock market of both countries.

Table 4.5. Return Predictability

The table reports the results of the predictive regression: $r_{t+1} = \alpha + \beta z_t + \varepsilon_{t+1}$. The Newey-West t-statistics are reported in the parentheses. I suppress the sign of t-statistics. All predictors are from 1996M7-2015M12 except for the investor sentiment (IS), whose data is only available up to 2015M9. *, ** and *** indicate significance at the 10%, 5%, and 1% levels.

Predictors(z_t)	S&P 500			FTSE		
	$\beta(\%)$	t-stat	Adj$R^2(\%)$	$\beta(\%)$	t-stat	Adj $R^2(\%)$
LTR	0.14	0.60	0.10	0.23	1.02	0.32
INFL	-0.09	0.31	0.04	-0.25	1.12	0.37
LTY	-0.25	0.95	0.31	-0.20	0.86	0.23
SVAR	-0.69	1.77^{*}	2.32	-0.25	0.99	0.37
DE	0.04	0.08	0.01	0.06	0.14	0.02
DFY	-0.32	0.59	0.50	-0.16	0.47	0.15
TBL	-0.16	0.53	0.12	-0.04	0.24	0.00
DY	0.65	1.67^{*}	2.07	0.55	1.75^{*}	1.73
EP	0.26	0.52	0.34	0.20	0.52	0.23
TMS	0.01	0.01	0.00	-0.13	0.48	0.10
B/M	0.31	1.02	0.48	0.23	0.89	0.31
DP	0.58	1.28	1.65	0.49	1.50	1.40
NTIS	0.60	1.26	1.78	0.34	0.90	0.68
IS	-0.59	1.83^{*}	1.68	-0.51	1.97^{*}	1.40
FX	-0.97	2.72^{***}	4.16	-0.67	2.28^{**}	2.15

A clear result from Table 4.5 is that most predictors have negligible ability in forecasting the excess return. If risk premium is indeed time-varying, then the weak predictive relation is either due to wrongly selected variables, or lack of predictability during specific periods as discussed in Welch and Goyal (2008).[11] Strikingly, the Forex-specific factor, which is constructed solely from the foreign exchange market, significantly predict stock market risk premium of two countries with the

[11]They find that for the most recent 20 years up to their work, even the in-sample predictability is very poor.

Newey-West t-statistics 2.72 and 2.28 respectively. The sign of slope coefficient is also consistent with the estimates of $\lambda_{1x}, \lambda_{1x}^*$ in Table 4.2, higher FX_t will lower the aggregate risk premium in both countries.

A potential explanation for the commonality in the foreign exchange and stock markets within our sample periods may be due to the crisis. It's well known that the correlations among different asset classes will peak during the crisis periods, it's therefore worthwhile to investigate to what extent the predictability can be attributed to the comovements during the recession. More specifically, I run a predictive regression by controlling for a dummy variable that takes the value of 1 during the NBER recession periods.[12] In addition, I control for other predictors which may capture different risk of stock markets. report the incremental power of predicting the equity premium on top of each predictor by FX_t in Table 4.6. The strong predictability by the Forex-specific factor remains untouched after controlling for all other predictors including the recession dummy. Given the importance of the Forex-specific factor in accounting for exchange rate fluctuations, such remarkable performance from forecasting the aggregate stock return indicates that there exists common systematic risk between those two markets.

Intuitively, if Forex-specific factor indeed well captures the systematic risk, it shall also forecast risk premia of assets that may have different risk exposure. I thus use Forex-specific factor to forecast returns of a variety of industrial portfolios and characteristic portfolios. The results are presented in Table 4.7 and 4.8. The Forex-specific factor significantly predicts almost all industry portfolios except Shop and Utility. For portfolios constructed in the Fama-French five-factor model, the Forex-specific factor also predicts most of sorted portfolios, without significant cross-section pattern of loadings on the predictor. Noticeably, the estimated slope coefficients are all negative, same with the sign for market risk premium. In all, the forecasting exercise implies that the foreign exchange market provides important information about risk-return relation in the stock markets, and such information is

[12] Within our sample period, the NBER business cycle dates are March 2000 to November 2001 and December 2007 to June 2009.

Table 4.6. Bivariate Predictive Regression

The table reports the results of the bivariate predictive regression: $r_{t+1} = \alpha + \beta FX_t + \psi X_t + \varepsilon_{t+1}$. The Newey-West t-statistics are reported in the parentheses. I suppress the sign of t-statistics. All predictors are from 1996M7-2015M12 except for the investor sentiment (IS), whose data is only available up to 2015M9. *, ** and *** indicate significance at the 10%, 5%, and 1% levels.

Predictors(X)	S&P 500					FTSE				
	$\beta(\%)$	t-stat	$\psi(\%)$	t-stat	Adj. $R^2(\%)$	$\beta(\%)$	t-stat	$\psi(\%)$	t-stat	Adj. $R^2(\%)$
LTR	-0.97	2.61***	0.18	0.66	3.90	-0.67	2.22**	0.26	1.03	2.12
INFL	-1.00	2.75***	-0.22	0.96	3.97	-0.71	2.41**	-0.35	1.68*	2.42
LTY	-1.02	2.92***	-0.39	1.55	4.47	-0.71	2.39**	-0.30	1.27	2.23
SVAR	-0.85	2.83***	-0.49	1.30	4.84	-0.79	2.90***	-0.11	0.42	1.78
DE	-0.97	2.65***	-0.05	0.14	3.75	-0.64	2.17**	-0.10	0.35	1.75
DFY	-0.94	2.69***	-0.14	0.34	3.84	-0.67	2.22**	-0.06	0.19	1.73
TBL	-0.96	2.66***	-0.08	0.33	3.77	-0.66	2.19**	-0.04	0.11	1.73
DY	-0.92	2.39**	0.58	1.67*	5.37	-0.67	2.23**	0.01	0.04	3.16
EP	-0.96	2.57**	0.23	0.54	4.00	-0.63	2.04**	0.50	1.64	1.91
TMS	-1.04	2.83***	-0.26	0.87	4.06	-0.66	2.16**	0.18	0.46	2.30
B/M	-0.96	2.65***	0.27	1.01	4.10	-0.75	2.47**	-0.32	1.24	1.97
DP	-0.95	2.45**	0.55	1.44	5.22	-0.66	2.21**	0.20	0.79	3.01
NTIS	-0.86	2.62***	0.32	0.78	4.17	-0.65	2.12**	0.47	1.52	1.82
IS	-0.89	2.39**	-0.44	1.41	4.60	-0.60	1.91	-0.39	1.46	2.55
DUMMY	-0.85	2.50**	-0.02	1.20	4.83	-0.55	1.85	-0.02	1.75	3.13

orthogonal to commonly perceived stock market risk factors.

Table 4.7. Predictability of industry portfolios

The table reports the results of the predictive regression by using industry portfolios as the testing assets. The Newey-West t-statistics are reported in the parentheses. I suppress the sign of t-statistics. *, ** and *** indicate significance at the 10%, 5%, and 1% levels.

	$\beta(\%)$	t-stat	Adj. $R^2(\%)$
NoDurable	-0.65	2.57**	2.56
Durable	-1.17	2.05**	2.02
Manufacture	-1.01	2.43**	3.55
Energy	-0.89	2.29**	1.88
High-Technology	1.27	2.39**	2.35
Telecom	-1.00	2.57**	2.87
Shop	-0.42	1.36	0.43
Health	-0.57	2.07**	1.35
Utility	-0.41	1.18	0.53
Other	-0.95	2.02**	2.66

4.5.2 Long-horizon predictability

This subsection evaluates whether the Forex-specific factor has forecasting power over longer horizons. Since Forex-specfic factor enters into the pricing kernel, it shall not only has predictive power on returns of different assets (as shown in the

Table 4.8. Predictability of characteristic portfolios

The table reports the results of the predictive regression by using characteristic portfolios as the testing assets. The Newey-West t-statistics are reported in the parentheses. I suppress the sign of t-statistics. *, ** and *** indicate significance at the 10%, 5%, and 1% levels.

Panel A: Size

	$\beta(\%)$	t-stat	Adj $R^2(\%)$
Small	-0.95	1.87*	1.75
2	-0.67	1.37	0.54
3	-0.71	1.61	0.87
4	-0.81	2.01**	1.43
5	-0.90	2.11**	1.90
6	-0.86	2.25**	2.12
7	-0.92	2.23**	2.62
8	-0.80	1.90*	1.84
9	-0.98	2.42**	3.85
Large	-0.95	2.95***	4.09

Panel B: Book to market

	$\beta(\%)$	t-stat	Adj $R^2(\%)$
Growth	-1.00	2.65***	3.50
2	-0.66	1.86*	1.65
3	-0.77	2.71***	2.66
4	-0.92	2.14**	3.19
5	-0.58	1.60	1.09
6	-0.87	2.07**	2.76
7	-0.75	1.79*	2.30
8	-0.85	1.53	2.68
9	-0.83	1.97**	2.40
Value	-0.91	1.68*	1.63

Panel C: Momentum

	$\beta(\%)$	t-stat	Adj. $R^2(\%)$
Loser	-2.16	3.18***	4.12
2	-1.10	2.14**	1.92
3	-0.95	2.38**	2.17
4	-0.91	2.38**	2.75
5	-0.80	2.28**	2.52
6	-0.95	2.99***	4.17
7	-0.76	2.82***	2.78
8	-0.74	2.18**	2.62
9	-0.85	2.22**	3.04
Winner	-1.05	2.11**	2.23

Panel D: Investment

	$\beta(\%)$	t-stat	Adj. $R^2(\%)$
Low	-0.90	2.07**	2.49
2	-0.93	2.20**	3.14
3	-0.63	1.99**	1.76
4	-0.71	2.05**	2.25
5	-0.83	2.28**	3.10
6	-0.81	2.68***	3.69
7	-0.80	2.62***	3.00
8	-0.80	2.10**	2.30
9	-1.14	2.86***	3.44
High	-1.14	2.35**	3.09

Panel E: Profitability

	$\beta(\%)$	t-stat	Adj. $R^2(\%)$
Low	-1.21	2.07**	2.27
2	-1.01	2.13**	3.04
3	-0.90	2.40**	3.19
4	-0.99	2.45**	3.63
5	-0.84	2.46**	2.73
6	-0.88	2.21**	2.60
7	-1.04	2.44**	4.08
8	-0.84	2.86***	3.07
9	-0.72	2.42**	2.46
High	-0.82	2.61***	3.29

previous subsection), but also predicts the multi-period risk premium of a single asset. Therefore I run the long-horizon predictive regression on market return under different holding periods to test the long-run predictability.

Table 4.9 reports the in-sample forecasting results for stock market excess returns of two countries. The table shows that the Forex-specific factor can consistently predict the short and long run market risk premium, with horizons ranging from one month to three years. The short term predictability peaks at around one-quarter horizon, while that for long term (over one year) peaks at three-year horizon. For S&P 500 index, the Forex-specific factor explains almost 10% variance of the one quarter ahead cumulative excess return, while for FTSE index, such factor has relatively less predictive power but still with noteworthy adjusted R^2 5.94%. Even at three-year horizon, the adjusted R^2 can reach 8.01% and 12.5% for both markets.

Table 4.9. Long Horizon Return Predictability

The table reports the results of the long-horizon predictive regression $\frac{1}{h}\sum_{i=1}^{h} r_{t,t+i} = \alpha + \beta FX_t + \varepsilon_{t+1}$. The Newey-West t-statistics are reported in the parentheses. I suppress the sign of t-statistics. * , ** and *** indicate significance at the 10%, 5%, and 1% levels.

Horizon(h)	S&P 500		FTSE		S&P 500 on Dollar factor	
	β(%)(t-stat)	Adj R^2(%)	β(%)(t-stat)	Adj R^2(%)	β(%)(t-stat)	Adj R^2(%)
1	-0.97(2.72)***	4.16	-0.67(2.28)**	2.15	-0.14(0.35)	-0.33
2	-0.87(2.09)**	6.46	-0.62(1.98)**	4.07	0.02(0.06)	-0.43
3	-0.86(2.23)**	9.51	-0.59(2.07)**	5.69	-0.11(0.38)	-0.26
4	-0.76(2.20)**	9.39	-0.53(1.94)*	5.94	-0.06(0.20)	-0.38
5	-0.69(2.24)**	9.21	-0.48(1.98)**	5.79	-0.04(0.17)	-0.41
6	-0.64(2.29)*	9.12	-0.44(1.96)*	5.59	-0.03(0.17)	-0.41
9	-0.46(2.16)**	6.45	-0.31(1.79)*	3.77	0.06(0.50)	-0.34
12	-0.36(1.94)*	5.16	-0.22(1.43)	2.26	0.09(0.96)	-0.08
24	-0.24(1.14)	3.83	-0.21(1.04)	3.85	0.05(0.67)	-0.26
36	-0.27(2.04)**	8.01	-0.29(2.23)**	12.5	0.01(0.19)	-0.49

Boudoukh et al. (2008) finds that the slope coefficients of long and short horizon predictive regression are highly correlated if the predictor is persistent, thus result of long run regression does not provide much new insight beyond that of short run predictive regression. They show that the correlation between the slope coefficient of one-period and that of k-period predictive regression is:

$$\frac{(1-\rho)^2+\rho(1-\rho)(1-\rho^{k-1})}{(1-\rho)\sqrt{k(1-\rho)^2+2\rho[(k-1)-\rho(k-\rho^{k-1})]}}. \tag{4.5.2}$$

The estimated persistence of Forex-specific factor is 0.82, therefore equation

(4.5.2) implies that the correlations between one-month and 1,2,3 year slope coefficients are 0.58, 0.40 and 0.31, respectively. In particular, the coefficient for three-year horizon is moderately correlated with that of one month horizon, yet both are significant at 5% level, with the Newey-West t-statistics 2.72 and 2.04 for U.S. and 2.28 and 2.23 for U.K.. Those results suggest that the long horizon slope coefficient is not a repetition of short run estimates, but instead uncovers the predictive power of the Forex-specific factor for stock markets at the long run.

4.5.3 Cross-section of industry portfolios

Francis et al. (2008) finds that even though currency risk is significantly priced at the aggregate market, it's puzzling why such risk does not show up at the industry level since numerous studies investigate the exchange rate effects on industries. Having discussed the impact of Forex-specific factor on aggregate stock market from the time-series predictability, it's then of interest to see its explanatory power for the cross-section return differences in the industry portfolios.

Following a long literature of cross-section stock returns, I examine the following model using 30 industry portfolios as testing assets:[13]

$$E[R^i] = \alpha^i + \beta^i_M \lambda_{MKT} + \beta^i_{SMB} \lambda_{SMB} + \beta^i_{HML} \lambda_{HML} + \beta^i_{RMW} \lambda_{RMW} + \beta^i_{CMA} \lambda_{CMA} + \beta^i_{FX} \lambda_{FX}, \tag{4.5.3}$$

where R^i is the excess return of i-th industry portfolio, and MKT, SMB, HML, RMW, CMA represent the five factors recently proposed by Fama and French (2015). I use traditional cross-sectional regression approach for estimating (4.5.3). In the first step, I estimate the factor betas by running the time-series regression of excess returns on six factors. In the second step, I estimate the cross-sectional regression using mean excess return and the factor betas obtained from the first step. Note that controlling for other commonly used factors helps pin down the importance of Forex-specific factor for explaining the cross-sectional differences of industry portfolio returns.

[13]Data of industry portfolios are available from Kenneth French's website.

For comparison, I also report the results when only market factor or Fama-French three factors are used respectively.

Table 4.10 presents the estimation results. First, the classical CAPM or Fama-French three-factor model can't explain the difference in average returns of industry portfolios. The adjusted R^2 of cross-sectional regression is low. This is consistent with estimates in Lewellen et al. (2010), who find that adding 30 industry portfolios as testing assets will substantially deteriorate the pricing ability of many celebrated models. A striking result emerges when I add Forex-specific factor as a cross-sectional risk factor. Even the original CAPM model now has much larger explanatory power for cross-section return dispersions, with adjusted R^2 jumping from 4.3% to 41.9%, while the incremental power for Fama-French three-factor model is also remarkable, from 21.1% to 39.7%. Another observation is that the most recent Fama-French five-factor model performs well and increases the adjusted R^2 by twofold compared to that of the three-factor model. Fama and French (2016) find that adding profitability (*RMW*) and investment (*CMA*) factors help alleviate several well-known cross-section average return anomalies. The results here suggest that those two additional factors are also useful for explaining cross-industry return differences. Interestingly, the classical CAPM augmented with the Forex-specific factor has almost the same explanatory power with the five-factor model, this indicates that the Forex-specific factor is also an important risk factors at the cross-section dimension.

From the estimation of full specification (4.5.3), I find that the predictive power of FX factor is partially subsumed in the CMA factor, yet it still provides additional information since the adjusted R^2 rises from 42.7% to 45.1%. The fact that the investment factor and the Forex-specific factor contain common information about stock returns suggests that the Forex-specific factor may affect the cash-flow part of stock prices since common measures used to construct investment factor (e.g. the total asset growth as in Fama and French (2015)) is closely related to firms's cash flow. Indeed as I will show in the next subsection, by decomposing the return into

Table 4.10. Cross-section Predictability

The table reports the cross-sectional regression results. MKT, SMB, HML, RMW and CMA are the Fama-French five factors, FX is the Forex-specific factor. Shanken (1992) corrected t-statistics are reported in the parentheses. I suppress the sign of t-statistics. *, ** and *** indicate significance at the 10%, 5%, and 1% levels.

	Constant	MKT	SMB	HML	RMW	CMA	FX	Adjusted R^2(%)
1	0.013	-0.003						4.3
t-stat	(2.35)**	(0.99)						
2	0.013	-0.003					0.506	41.9
t-stat	(2.09)**	(0.93)					(1.57)	
3	0.017	-0.003	-0.004	-0.003				21.1
t-stat	(5.01)***	(0.75)	(0.73)	(0.95)				
4	0.013	-0.001	-0.002	-0.001			0.448	39.7
t-stat	(4.93)***	(0.32)	(0.31)	(0.36)			(1.57)	
5	0.012	0.001	-0.002	-0.003	0.001	0.005		42.7
t-stat	(5.29)***	(0.03)	(0.37)	(0.58)	(0.22)	(1.07)		
6	0.012	0.001	-0.001	-0.002	0.001	0.004	0.251	45.1
t-stat	(5.02)***	(0.07)	(0.26)	(0.31)	(0.15)	(0.94)	(0.89)	

the discount rate and cash flow parts, the Forex-specific factor strongly forecasts the cash-flow news of stock returns.

In Figure 4.3, I plot the portfolios' mean excess return versus their factor loadings on the Forex-specific factor after controlling for Fama-French five factors. The industry returns line up relatively well, meaning that the exposure to Forex-specific factor indeed help explain the cross-sectional differences in average returns of industry portfolios. Therefore, all above results demonstrate on the one hand the cross-sectional predictive ability of Forex-specific factor for stock market, and on the other hand the existence of currency-related risk premia in the industry level.

4.5.4 Return decomposition

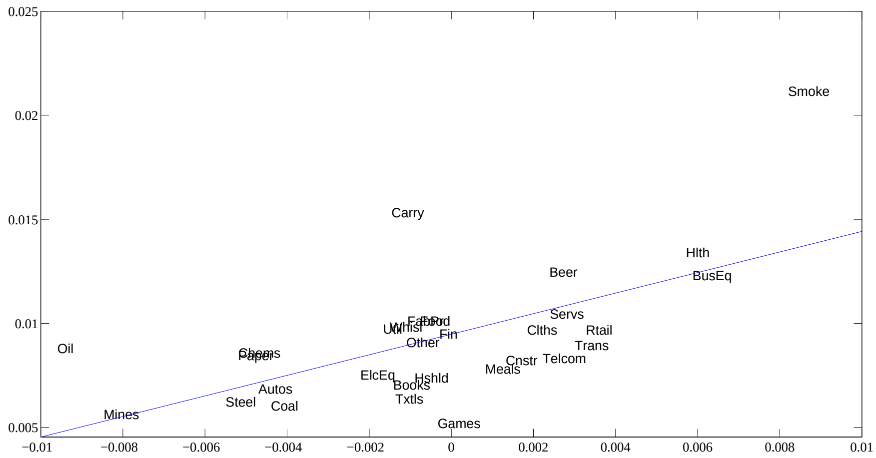
To gain more insights about the origin of predictability by the Forex-specific factor, I work with Campbell and Shiller (1988) decomposition:[14]

$$r_{t+1} - E_t r_{t+1} = (E_{t+1} - E_t)\sum_{j=0}^{\infty}\rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t)\sum_{j=0}^{\infty}\rho^j \Delta r_{t+1+j}, \quad (4.5.4)$$

[14] Due to lack of U.K. stock market data, I only implement such decomposition for U.S. market.

Figure 4.3. Industry average excess returns versus FX Beta

The figure plots the scatter between the average excess returns of 30 industry portfolios and their loadings on Forex-specific factor after controlling for exposures to Fama-French five factors.



where $\rho = \frac{1}{1+\exp(\bar{dp})}$. Denote unexpected return, cash flow news and discount rate news as $\eta^r_{t+1}, \eta^{CF}_{t+1}, \eta^{DR}_{t+1}$, then equation (4.5.4) becomes:

$$\eta^r_{t+1} = \eta^{CF}_{t+1} - \eta^{DR}_{t+1}. \tag{4.5.5}$$

Following Rapach et al. (2016b) and a large literature, the news component can be extracted from a VAR model with state $X_t = [r_t, dp_t, z_t]$:

$$X_{t+1} = \mu + AX_t + u_{t+1}, \tag{4.5.6}$$

where r_t is the market excess return, dp_t is the log dividend-price ratio, z_t is some additional state characterizing the economy beyond dividend-price ratio.[15] Denote the 0-1 selection vector e_1, whose elements are all zero except the position that corresponds to market excess return. We identify the discount rate news from VAR model (4.5.6) directly, and take the residual as the cash flow news. In other words,

[15]Following Rapach et al. (2016b), I choose z_t from predictors that appear in Welch and Goyal (2008).

the news component can be estimated as:[16]

$$
\begin{aligned}
\eta^{r}_{t+1} &= e_1^{'} u_{t+1}, \\
\eta^{DR}_{t+1} &= e_1' \rho A (I-\rho A)^{-1} u_{t+1}, \\
\eta^{CF}_{t+1} &= \eta^{DR}_{t+1} + \eta^{r}_{t+1},
\end{aligned}
$$

Then I estimate the following regressions after obtaining the news component:

$$
\begin{aligned}
E_t r_{t+1} &= \alpha_E + \beta_E FX_t + \varepsilon^{E}_{t+1}, \\
\eta^{CF}_{t+1} &= \beta_{CF} FX_t + \varepsilon^{CF}_{t+1}, \\
\eta^{DR}_{t+1} &= \beta_{DR} FX_t + \varepsilon^{DR}_{t+1},
\end{aligned}
\tag{4.5.7}
$$

where $E_t r_{t+1} = e_1'(\mu + AX_t)$.

Comparing the magnitude of slopes in system (4.5.7), it's then straightforward to check the source of predictability. More specifically, $\beta_E, \beta_{CF}, \beta_{DR}$ characterize the predictive ability of the Forex-specific factor on the expected return, cash flow news and discount rate news. We report the regression results in Table 4.11. The Forex-specific factor has a strong predictive ability on the news of future cash flows, which is robust across different conditioning variables z_t. Even though FX factor is modeled as a driving force of stochastic discount factor, the ability of forecasting news of future cash flows is not inconsistent with the model. In many asset pricing models where investor has either CRRA or the Epstein-Zin preference, the log SDF is connected to the consumption growth, whose variation is clearly linked to that of future cash flows of contingent claims. In addition, the predictability of cash flow news is in line with the findings documented by Atanasov and Nitschka (2015). In an ICAPM framework, they show that a common source of systematic risk in stock and currency returns is reflected in the market return's cash-flow news.

[16]Chen and Zhao (2009) show that the identification scheme may be problematic if there are any misspecifications in the predictability. It will affect the estimated discount rate news directly and cash flow news indirectly. Following a remedy by Maio and Philip (2015), I repeat the exercise by first identifying the cash flow news, and treat the rest as discount rate news. The results are quantitatively similar.

Simultaneously, the FX factor also predicts significantly the news of discount rate for many conditioning variables. Conforming to the intuition, the predictive relation is opposite for cash-flow news and discount-rate news, meaning that a positive cash-flow news will be accompanied by a negative discount rate news, or a lower risk premium.

Table 4.11. Source of predictability

The table reports the results of return decomposition. The Newey-West t-statistics are reported in the parentheses. *, ** and *** indicate significance at the 10%, 5%, and 1% levels.

z_t	$\beta^E(\%)$	$\beta^{CF}(\%)$	$\beta^{DR}(\%)$
No predictor	-0.11	-0.39	0.47
	(-1.01)	(-2.40)**	(2.07)**
DY	-0.09	-0.40	0.48
	(-0.81)	(-2.64)***	(2.02)**
EP	-0.12	-0.87	-0.02
	(-0.99)	(-1.81)*	(-0.09)
DE	-0.12	-0.87	-0.02
	(-0.99)	(-1.81)*	(-0.09)
BM	-0.10	-0.42	0.44
	(-0.96)	(-2.30)**	(1.74)*
TBL	-0.09	-0.40	0.47
	(-0.80)	(-2.67)***	(2.01)**
DFY	-0.32	-0.64	0.00
	(-1.90)*	(-2.65)***	(0.01)
LTY	-0.14	-0.47	0.36
	(-1.27)	(-2.76)***	(1.55)
TMS	-0.03	-0.40	0.53
	(-0.30)	(-2.38)**	(2.45)**
NTIS	-0.50	-0.25	0.22
	(-2.84)***	(-1.92)*	(0.68)
INFL	-0.11	-0.39	0.47
	(-1.04)	(-2.42)**	(2.07)**
LTR	-0.11	-0.39	0.47
	(-1.06)	(-2.42)**	(2.02)**
DFR	-0.11	-0.39	0.47
	(-1.09)	(-2.41)**	(2.10)**
SVAR	-0.27	-0.32	0.38
	(-1.80)*	(-1.99)**	(1.94)*
IS	-0.15	-0.39	0.46
	(-1.27)	(-2.83)***	(1.64)

4.5.5 Variance of log SDF

The model in this paper allows for explicit computation of higher order cumulants as in Backus et al. (2001). According to their definition and pricing kernel equation (4.2.6):

$$\text{Higher-order cumulants} = \log E_t(M_{t+1}) - E_t \log(M_{t+1}) = \frac{1}{2}\lambda_t^{'}\lambda_t. \tag{4.5.8}$$

In particular, since the SDF is conditionally log-normal, the higher-order cumulants simply reduce to the conditional variance of log SDF $\frac{1}{2}Var_t[m_{t+1}]$.

We plot the standardized conditional variance of log SDF and Forex-specific factor in Figure 4.4. The figure shows that the variance of log SDF are almost entirely driven by the Forex-specific state, the correlation reaches 0.99. The dominant role can be attributed to the much higher volatility of Forex-specific factor comparing with other observable states. Being a significant driving force of the conditional variance of log SDF sheds light on the source of predictability on stock risk premium. The conditional variance of log SDF is an (infeasible) predictor of aggregate market in even a simple textbook economy where agent has the Epstein-Zin preference and the log return and log SDF are jointly normal. For example, consider the asset pricing equation for return of claim to aggregate consumption R^c_{t+1}:

$$E_t[M_{t+1}R^c_{t+1}] = 1. \tag{4.5.9}$$

Assume that M_{t+1} and R^c_{t+1} are conditionally log-normal, then above equation reduces to:

$$E_t(r_{t+1}) - r_t^f = -\frac{1}{2}Cov_t(m_{t+1}, r^c_{t+1}) - \frac{1}{2}Var_t(r^c_{t+1}), \tag{4.5.10}$$

where small letters denote the logarithm quantities. When investor has Epstein-Zin preference:

$$U_t = \{(1-\beta)C_t^{\frac{1-\gamma}{\theta}} + \beta(E_t U_{t+1}^{1-\gamma})^{\frac{1}{\theta}}\}^{\frac{\theta}{1-\gamma}}, \tag{4.5.11}$$

where $\theta = \frac{1-\gamma}{1-\frac{1}{\psi}}$, the log SDF can be written as:

$$m_{t+1} = \theta \log \beta - \frac{\theta}{\psi} g_{t+1} + (\theta - 1) r_{c,t+1}. \tag{4.5.12}$$

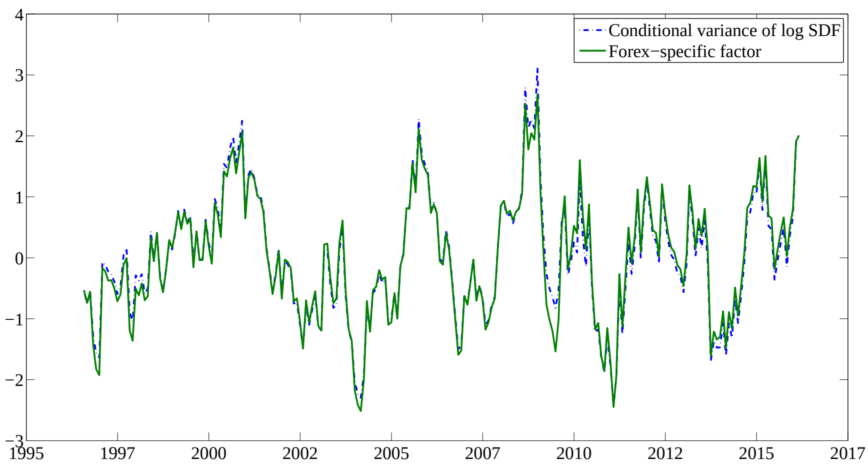
Combining (4.5.12) and (4.5.10), I thus have:

$$E_t(r_{t+1}) - r_t^f = -\frac{1}{2(\theta-1)} Var_t(m_{t+1}) - \frac{\theta}{2\psi(\theta-1)} Cov_t(m_{t+1}, g_{t+1}). \tag{4.5.13}$$

From equation (4.5.13), it's now clear that any factors driving the conditional variance of log SDF shall be good candidate for predicting risk premium.

Figure 4.4. Conditional variance of log SDF and Forex-specific factor

The figure plots the standardized conditional variance of model generated log SDF and the standardized Forex-specific factor.



However, it shall be noted that the reduced form stochastic discount factor (4.2.6) may not mimic the SDF in this simple economy, therefore above explanation is not consistent with the empirical findings in previous subsections. Nevertheless, I show below that the evidence of predictability can still be reconciled with a complicated equilibrium model.

To make the model tractable, I work within the continuous time framework. Notice that the continuous counterpart of (4.2.6) is:

$$\frac{d\pi_t}{\pi_t} = -r_t dt - \lambda_t' dW_t, \tag{4.5.14}$$

where λ_t is given in (4.2.7). We consider the case with only one state variable $Z_t = x_t$, which follows an OU process with zero mean:

$$dx_t = -\kappa x_t dt + \sigma F dW_t, \tag{4.5.15}$$

where F is $1 \times m$ vector, with $FF' = 1$. W_t is a m-dimensional Brownian Motion.

Define an auxiliary state $y_t = x_t^2$, the dynamics of y_t can be found by applying Itô's lemma on (4.5.15):

$$dy_t = (\sigma^2 - 2\kappa y_t)dt + 2\sigma\sqrt{y_t}F dW_t. \tag{4.5.16}$$

Assume that the process for consumption is:

$$\frac{dC_t}{C_t} = \mu dt + \sqrt{y_t} L dW_t, \tag{4.5.17}$$

where L is $1 \times m$ vector, with $LL' = 1$. Household has Epstein-Zin preference:

$$J_t = \max_{\{C_s\}} E_t\left(\int_t^T f(C_s, J_s) ds\right), \tag{4.5.18}$$

where the aggregator $f(C,J)$ is given by:

$$f(C,J) = \frac{\beta(1-\gamma)}{1-\frac{1}{\psi}} J\left(\left(\frac{C}{((1-\gamma)J)^{\frac{1}{1-\gamma}}}\right)^{1-\frac{1}{\psi}} - 1\right). \tag{4.5.19}$$

Then I have the following proposition:

PROPOSITION 4. *Suppose the endowment economy is described as above, then the dynamics of equilibrium state price of density is:*

$$\frac{d\pi_t}{\pi_t} = -r_t dt - \lambda_t F dW_t. \tag{4.5.20}$$

The risk premium of consumption claim is:

$$E_t(\frac{dP_t}{P_t}) + \frac{D_t}{P_t}dt - r_t dt = 4\frac{1-\psi}{1-\gamma}A_1\sigma\frac{\lambda_t^2 - \lambda_t\lambda_0}{\lambda_1}KF' - \frac{\lambda_t^2 - \lambda_t\lambda_0}{\lambda_1}KL', \quad (4.5.21)$$

where $\lambda_t = \lambda_0 + \lambda_1 x_t$*,* F, K, L, A_1 *are given in the appendix.*

The proposition confirms that in this endowment economy, the reduced form SDF (4.2.6) is an equilibrium outcome and the property that stock risk premium is a linear function of conditional variance of log SDF (λ_t^2) is preserved. To the best of our knowledge, the equilibrium motivation for specification (4.2.6) has not been discussed before. Given the popularity of (4.2.6) in the literature of affine term structure model, it's important to have a micro-founded explanation for that specification.[17]. Also, according to this proposition, the predictability results presented in previous subsections should be an equilibrium regularity, once I have a correct model of stochastic discount factor.

4.6 Additional Implications

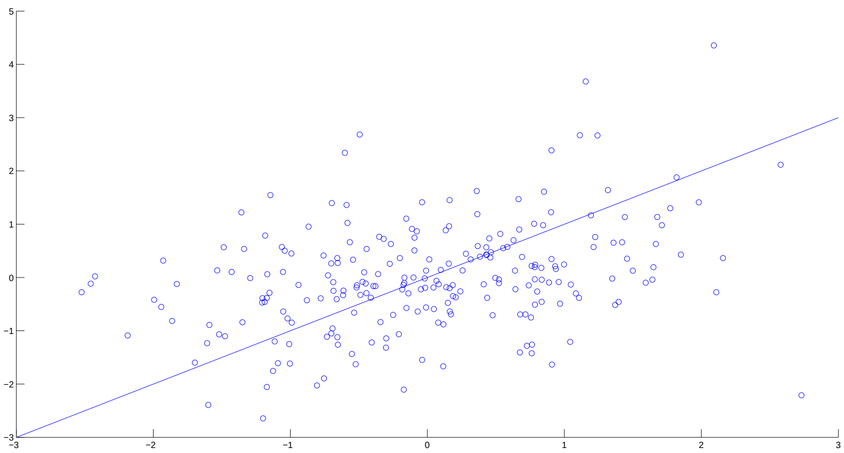
4.6.1 Systematic risk factor from nonparametric method

A recent paper by Verdelhan (2016) confirms the existence of systematic risk in a number of bilateral exchange rates. He finds that the dollar factor, which is constructed as the average of all currency returns at each time period, is the main determinants of world-wide exchange rate fluctuations. It will be interesting to compare the dollar factor with the Forex-specific factor obtained in this paper. Note that his method of extracting the factor is non-parametric, while ours relies on a fully parametrized SDF model. As can be seen from the scatter plot in Figure 4.5, those two factors identified using different methods are positively correlated with

[17] Bansal and Zhou (2002) also discusses an equilibrium explanation for exogenous specified pricing kernel, their method is to specify a process for r^c_{t+1} such that (4.5.12) coincides with (4.2.6) Here I use a bottom-up strategy by specifying a consumption process, and show that the equilibrium pricing kernel is of form (4.2.6).

the correlation coefficient of 0.32. This again provides support for the interpretation of Forex-specific factor as a systematic risk component. Moreover, Verdelhan (2016) shows that the Dollar factor depends on U.S.-specific shocks to pricing kernels, I therefore compare its ability on driving expected return of U.S. stock market with that of Forex-specific factor over different forecasting horizons in the last two columns of Table 4.9. The results of the long-horizon predictive regression shows that the Dollar factor has almost no explanatory power for U.S. stock market. This highlights the usefulness of the parametrized SDF model in extracting important risk factors.

Figure 4.5. Forex-specific versus Dollar factor



4.6.2 Forward premium anomaly

In this subsection, I explore how well the model can account for the forward premium anomaly as documented by Fama (1984). In the sample studied here, the UIP regression

$$\Delta s_{t+1} = \alpha + \beta(r_t - r_t^*) + \varepsilon_{t+1} \tag{4.6.1}$$

gives β estimate of -1.62, with a t-statistic 0.93 and adjusted R^2 -0.06%. Theory indicates that if both currencies are equally risky, then investors expect the currency with high interest rates to depreciate, thus β shall be positive. The deeply negative

β generates the so-called forward premium anomaly (or UIP puzzle). Fama (1984) attributes the anomaly to the existence of time-varying risk premium. If this is the case, then the risk-adjusted UIP regression shall be used instead of (4.6.1):

$$\Delta s_{t+1} = \alpha + \beta(r_t - r_t^*) + \gamma rp_t + \varepsilon_{t+1}. \tag{4.6.2}$$

Within the affine model, the risk premium term can be explicitly solved out:

$$rp_t = \frac{1}{2}(\lambda_t^{'}\lambda_t - \lambda_t^{*'}\lambda_t^*). \tag{4.6.3}$$

Estimating model (4.6.2) gives $\hat{\beta} = -0.72$ with a t-statistic 0.40, adjusted R^2 now increases to 0.88%. Though the model is insufficient to fully account for the anomaly, to some extent the model implied risk premium does help alleviate it. The limited explanatory power for UIP puzzle is due to two reasons. First, one focus of this paper is to construct a parsimonious model that can track the dynamics of bond yield and exchange rates return. Thus our approach is different from Sarno et al. (2012) and Brennan and Xia (2006), who focus on resolving the forward premium anomaly and directly model the foreign exchange risk premium. In particular, I don't impose restrictions on λ_t and λ_t^* to possibly reconcile the forward premium anomaly, instead I motivate the restrictions through the literature of international shock transmission. The second and more important reason is that the model implied risk premium is a deterministic function of observable states and the Forex-specific factor. The former are exogenously given, while the latter is required to match the fluctuations of exchange rate return and option implied variance. Thus it's not obvious that the risk premium identified in the model can also satisfy conditions proposed by Fama (1984) as necessary to explain the forward premium anomaly.[18] Yet combing the less negative estimate of β in (4.6.2) and the strong predictive ability on stock market risk premium of both countries by Forex-specific factor, the model indeed captures important systematic risk.

[18] Two conditions are: i) the implied risk premium is more volatile than, and ii) negatively correlated with the interest rate differentials.

4.7 Conclusion

This article studies the share of systematic risk between the foreign exchange and the stock market through the lens of an affine term structure model. I treat the commonly used bond risk factors and one latent Forex-specific factor as the states driving the stochastic discount factors of the two countries. The model has satisfactory fit for bond yields, exchange rate returns and currency option implied variance. The Forex-specific factor turns out to be a strong predictor for aggregate stock market risk premium. In addition, it also greatly enhances the pricing ability of the classical CAPM and Fama-French three-factor model for cross-section industry portfolios, the performance is even comparable with that of the newly proposed Fama-French five factor model. The return decomposition finds that the Forex-specific factor strongly predicts the cash-flow news of the aggregate market, and the cross sectional regression indicates that this factor shares the information with the investment factor. Therefore, the evidence from the time-series and the cross-section dimensions both points to the close relation between the Forex-specific factor and the cash-flow, and echoes the theoretical results in Colacito and Croce (2011) that the common long-run growth in consumption is a key elements for resolving several asset pricing puzzles in the stock and the foreign exchange markets.

The results in this paper show that there is important information about economy-wide risk compensation in the foreign exchange market. It's then of interest to see whether such information is important in many other asset markets and how it interacts with the macroeconomic fluctuations. Providing such analysis is beyond the scope of this article and therefore left to future research.

Chapter 5 Summary of Conclusions

In Chapter 2, I discuss a problem that high-minus-low return spreads of currency carry and momentum are hard to reconcile simultaneously. Many risk factors that work for carry do not work for momentum. My paper finds that exposures to the risk of US monetary policy uncertainty (MPU) have very strong explanatory power for cross-sectional return dispersion of carry and momentum, with cross-sectional R2 reaching 96%. The evidence is quite robust and in particular, invariant to using either the news-based US monetary policy uncertainty index of Baker et al. (2016), or the realized variance of US Treasury yields. To interpret the results, I use an extended intermediary based exchange rate model based on Gabaix and Maggiori (2015). Higher US MPU leads to higher uncertainty of funding cost or investment yield, which triggers position unwinding for an intermediary with financial frictions, at both long and short sides. Hence the return to currency that is being held goes down, but that being shorted goes up. I show that high (low) carry/momentum currencies are more favorable for the intermediary to hold (short). Thus the model is consistent with the positive high-minus-low return spreads of carry and momentum, and moreover, their different exposures to the risk of US MPU.

In Chapter 3, my central innovation is to introduce the inflation ambiguity into the conditional ICAPM and study the cross-sectional implications on the inflation risk in the stock market. The idea is simple: since ambiguity shocks serve as a perceived inflation shocks for the investor with ambiguity-averse preference, the usual inflation beta and ambiguity beta will be tied up endogenously. This can be shown from a consumption-based asset pricing model, and thus generates a new source of variations for the cross-sectional inflation risk premium due to the presence of ambiguity premium, even though there are no changes in the predictive relation of inflation on future market returns or economic growth. Empirically I find this mechanism works quite well and is indeed unrelated to the conditional ICAPM channel studied in Boons et al. (2017). The evidence is strong for both aggregate- and industry-level analysis. The market timing strategy also delivers economically large profit, based on the sign of nominal-ambiguity correlation.

In Chapter 4, I study the share of systematic risk between the foreign exchange and the stock markets through the lens of an affine term structure model. The analysis starts with a parametric model for the stochastic discount factor (SDF). I treat the commonly used bond risk factors and one latent Forex-specific factor as the states driving the SDF of the two countries. The model has satisfactory fit for bond yields, exchange rate returns and currency option implied variance. The Forex-specific factor turns out to be a strong predictor of aggregate stock market risk premium. In addition, it also greatly enhances the pricing ability of the classical CAPM and Fama-French three-factor model for cross-section industry portfolios, the performance is even comparable with that of the newly proposed Fama-French five-factor model. The return decomposition finds that the Forex-specific factor strongly predicts the cash-flow news of the aggregate market, and the cross sectional regression indicates that this factor shares the information with the investment factor. Therefore, the evidence from the time-series and the cross-section dimensions both points to the close relation between the Forex-specific factor and the cash-flow, and echoes the theoretical results in Colacito and Croce (2011) that the common long-run growth in consumption is a key elements for resolving several asset pricing puzzles in the stock and the foreign exchange markets.

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Appendix

5.1 Appendix for Chapter 1

5.1.1 Theoretical model based on interest rate ambiguity

Here I present a variation of the theoretical model, where I interpret the interest rate uncertainty as the model uncertainty, or *ambiguity*, instead of *risk*. Distinguishing these concepts has proven to be quite relevant for the asset pricing. The risk describes the scenario when the outcome is random but the distribution is known, while the ambiguity represents the case when neither the quantity nor its distribution is known. I show that the main theoretical predictions are preserved if the uncertainty is interpreted as the ambiguity.

All other settings are identical except two aspects. First, the US interest rate lays in the interval:

$$R \in [R_0 - \sigma, R_0 + \sigma], \tag{A.1}$$

which is generated from the point forecast of a set of potential models for R. R_0 is the forecast from the reference model, and σ captures the US monetary policy uncertainty (ambiguity). Second, the financier is risk-neutral but has min-max preference. She has the set (A.1) in mind and at time $t = 0$, she chooses her position

$-Q$ on USD by maximizing the expected one-period profit:

$$\max_{Q} \min_{R} \quad E_0[V_1] \tag{A.2}$$

$$s.t. \quad P_0(V_1 \leq 0) \leq \alpha. \tag{A.3}$$

The idea is that the financier evaluates the portfolio plans using the worst case model for R, which delivers the lowest expected profit. It can be shown that if α is small, the worst-case R when $Q > 0$ is:

$$R = R_0 + \sigma. \tag{A.4}$$

The worst-case belief becomes $R = R_0 - \sigma$ when $Q < 0$. The equilibrium portfolio choice can be summarized by the following proposition.

PROPOSITION 5. *If the foreign interest rate R^* and the growth of foreign demand for US asset g are such that:*

$$\frac{R^* F^{-1}(\alpha)}{g f_0} > R_0 + \sigma,$$

then the equilibrium currency holding is positive and $Q = \frac{(R_0+\sigma)^{-1} R^* F^{-1}(\alpha) - g f_0}{R^* + g}$. Moreover, Q decreases as σ increases. Vice versa when $Q < 0$.

The demand equation suggests that higher *MPU* dampens the magnitude of Q, or the position unwinding at both long and short positions. Hence by deriving similar steps, all implications can be preserved under this framework with ambiguity over US monetary policy.

5.1.2 Adjustment for transaction costs, calculation of idiosyncratic volatility and skewness

Following Menkhoff et al. (2012b) and many others, at the end of month $t+1$, and for currency i, if it leaves the sorted portfolio that is formed at month t after $t+1$, then the *net* excess return for the lowest portfolio (the portfolio being shorted) is computed as

$$rx^s_{t+1} = f^a_t - s^b_{t+1}, \tag{A.5}$$

where the superscripts a and b represent the ask and bid prices. For the long portfolios above the bottom one, the net excess returns are

$$rx^l_{t+1} = f^b_t - s^a_{t+1}. \tag{A.6}$$

On the other hand, if currency i does not leave the current portfolio, then the excess returns are computed as

$$rx^s_{t+1} = f^a_t - s_{t+1}, \quad rx^l_{t+1} = f^b_t - s_{t+1}. \tag{A.7}$$

To compute two measures of the limits to arbitrage for each currency i, I follow Filippou et al. (2017) by first extracting the residual series from the following asset pricing model

$$rx^i_t = \alpha^i + \beta^i_1 DOL_t + \beta_2 HML_{carry,t} + \varepsilon_{i,t}, \tag{A.8}$$

where DOL_t and $HML_{carry,t}$ are the daily dollar factor and the slope factor from carry trade portfolios. This asset pricing model is proposed by Lustig et al. (2011), and the regression is estimated by using daily data within each month. Then the currency i's idiosyncratic volatility and skewness at month-T are computed as

$$IV_{i,T} = \sqrt{\frac{\sum_{j=1}^{N_T} \hat{\varepsilon}^2_{i,d}}{N_T}}, \quad IS_{i,T} = \frac{\sum_{j=1}^{N_T} \hat{\varepsilon}^3_{i,d}}{N_T (IV_{i,T})^3}, \tag{A.9}$$

where N_T denotes the number of daily returns available during month-T.

5.1.3 Supplementary results

Table A.1. Statistics of alternative momentum portfolios

The table reports the statistics for the currency momentum portfolios, which are obtained by sorting on the realized excess returns over the previous 1- and 6-month periods. Alternatively, I form the momentum portfolios by sorting on the changes in log spot rates over the previous 1-, 3- and 6-month periods. All portfolios are rebalanced monthly, and the average monthly excess returns (in percentage) are net of transaction costs. The exposures to the risk of US *MPU* are computed from Equation (2.3.1). The standard errors are in parentheses and based on Newey and West (1987) with optimal lag selection following Andrews (1991). The returns and *MPU* betas of high-minus-low portfolios are also reported. The monotonicity of portfolio excess returns and *MPU* betas are tested via the monotonic relation (MR) test of Patton and Timmermann (2010), where the *p*-values are reported based on either five portfolios (brackets) or all pair-wise comparisons (parentheses). The null hypotheses for the tests are the monotonically increasing returns and decreasing betas respectively. The sample period is from January 1985 to August 2017.

	Mom 1-1		Mom 6-1		Mom 1-1 (spot)		Mom 3-1 (spot)		Mom 6-1 (spot)	
	r^e	β_{MPU}	r^e	β_{MPU}	r^e	β_{MPU}	r^e	β_{MPU}	r^e	β_{MPU}
L	-0.15	0.21	-0.07	0.27	-0.01	0.12	0.05	0.17	0.15	0.20
	(0.14)	(0.08)	(0.15)	(0.09)	(0.14)	(0.08)	(0.15)	(0.08)	(0.16)	(0.09)
2	0.12	0.10	0.08	0.08	0.03	0.19	-0.01	0.07	-0.02	0.12
	(0.12)	(0.07)	(0.12)	(0.07)	(0.13)	(0.06)	(0.12)	(0.08)	(0.12)	(0.07)
3	0.12	-0.04	0.13	-0.06	0.12	-0.04	0.16	0.00	0.14	-0.03
	(0.13)	(0.06)	(0.12)	(0.06)	(0.13)	(0.06)	(0.12)	(0.06)	(0.12)	(0.05)
4	0.21	-0.14	0.15	-0.05	0.15	-0.08	0.20	-0.04	0.16	-0.08
	(0.12)	(0.08)	(0.12)	(0.06)	(0.13)	(0.07)	(0.13)	(0.05)	(0.12)	(0.07)
H	0.39	-0.12	0.41	-0.26	0.32	-0.13	0.25	-0.17	0.24	-0.23
	(0.13)	(0.09)	(0.14)	(0.10)	(0.13)	(0.09)	(0.13)	(0.10)	(0.13)	(0.09)
HML	0.54	-0.34	0.47	-0.53	0.33	-0.25	0.20	-0.34	0.09	-0.43
	(0.14)	(0.15)	(0.15)	(0.17)	(0.14)	(0.16)	(0.15)	(0.16)	(0.15)	(0.16)
MR	[0.97]	[1.00]	[1.00]	[0.99]	[0.99]	[0.99]	[0.48]	[0.93]	[0.39]	[0.81]
	(0.97)	(0.98)	(1.00)	(0.95)	(0.99)	(0.89)	(1.00)	(0.54)	(1.00)	(0.79)

Table A.2. Asset pricing test of alternative momentum portfolios

The table reports the results of asset pricing test for the two-factor model containing the dollar factor and the US *MPU* risk (u_t^{MPU}). The testing assets are three types of currency momentum portfolios (or joint with carry portfolios), which are obtained by sorting on the realized excess returns over the previous 1- and 6-month periods, or by sorting on the realized log changes in spot rates over the past 1-month. Panel A displays the results using Fama-MacBeth regression, where I report the estimated risk prices, cross-sectional OLS R^2, the heteroskedastic and autocorrelation consistent (HAC) standard errors based on Newey and West (1987) with optimal lag selection following Andrews (1991) (NW), and the Shanken-adjusted standard errors of Shanken (1992) (Sh). The *p*-values of χ^2-test on the null hypothesis that the pricing errors are jointly zero are also reported. Panel B displays the results of test via the GMM estimation, where I report the estimated factor loadings in the SDF model (2.3.5) by using either the identity matrix (GMM1) and the optimal weight matrix (GMM2) in the estimation. The Newey-West standard errors are in parentheses. I also report the the *p*-values from the χ^2-test, and the estimated Hansen-Jagannathan distance and its *p*-values, which are obtained via simulation. The sample period is from January 1985 to August 2017.

	Momentum 1-1			Momentum 6-1			Momentum 1-1 (spot)		
				Panel A: Fama-MacBeth					
	λ_{DOL}	λ_{MPU}	R^2	λ_{DOL}	λ_{MPU}	R^2	λ_{DOL}	λ_{MPU}	R^2
	0.14	-1.17	0.77	0.14	-0.86	0.93	0.13	-0.84	0.74
(NW)	(0.11)	(0.33)		(0.11)	(0.29)		(0.11)	(0.38)	
(Sh)	(0.11)	(0.51)		(0.11)	(0.39)		(0.11)	(0.49)	
χ^2_{NW}	[0.01]			[0.61]			[0.17]		
χ^2_{Sh}	[0.22]			[0.79]			[0.40]		
				Joint with carry					
	0.13	-1.36	0.86	0.13	-1.09	0.87	0.13	-1.20	0.83
(NW)	(0.11)	(0.31)		(0.11)	(0.31)		(0.11)	(0.27)	
(Sh)	(0.11)	(0.51)		(0.11)	(0.45)		(0.11)	(0.42)	
χ^2_{NW}	[0.00]			[0.00]			[0.02]		
χ^2_{Sh}	[0.21]			[0.20]			[0.47]		
				Panel B: GMM					
	b_{DOL}	b_{MPU}	R^2	b_{DOL}	b_{MPU}	R^2	b_{DOL}	b_{MPU}	R^2
GMM1	0.03	-1.17	0.77	0.03	-0.86	0.93	0.03	-0.84	0.74
s.e.	(0.04)	(0.62)		(0.03)	(0.42)		(0.03)	(0.56)	
GMM2	0.03	-0.90	0.72	0.04	-0.86	0.88	0.03	-0.50	0.60
s.e.	(0.04)	(0.57)		(0.03)	(0.39)		(0.03)	(0.45)	
χ^2-test	[0.23]			[0.81]			[0.26]		
HJ-dist	0.16			0.07			0.11		
	[0.03]			[0.52]			[0.31]		
				Joint with carry					
GMM1	0.03	-1.36	0.86	0.03	-1.09	0.87	0.03	-1.20	0.83
s.e.	(0.04)	(0.59)		(0.04)	(0.46)		(0.04)	(0.55)	
GMM2	0.03	-1.05	0.80	0.03	-1.23	0.85	0.03	-0.80	0.74
s.e.	(0.04)	(0.50)		(0.04)	(0.41)		(0.04)	(0.44)	
χ^2-test	[0.13]			[0.27]			[0.22]		
HJ-dist	0.28			0.22			0.22		
	[0.01]			[0.08]			[0.04]		

Table A.3. Horse race with other uncertainties on pricing carry trade

The table reports the results of asset pricing test on the three-factor model containing the dollar factor, US *MPU* risk, and shock to one of the uncertainty measures. The testing assets are five carry portfolios. The uncertainty proxies include the global FX volatility of Menkhoff et al. (2012a), VIX, the economic and the category-specific policy uncertainty indexes of Baker et al. (2016), and US Financial, Macro and Real denote three types of uncertainty measures constructed by Jurado et al. (2015) for US economy. The results are obtained via Fama-MacBeth regression, where I report the estimated risk prices, cross-sectional OLS R^2, the heteroskedastic and autocorrelation consistent (HAC) standard errors based on Newey and West (1987) with optimal lag selection following Andrews (1991) (NW), and the Shanken-adjusted standard errors of Shanken (1992) (Sh). The *p*-values of χ^2-test on the null hypothesis that the pricing errors are jointly zero are also reported. The sample period is from January 1985 to August 2017.

X	FX VOL		VIX		EPU		Taxes		Fiscal & spending	
λ_X	-0.59	0.16	-0.92	-0.24	-1.10	-0.18	-1.52	0.28	-1.22	0.12
(NW)	(0.18)	(0.30)	(0.27)	(0.41)	(0.36)	(0.42)	(0.47)	(0.75)	(0.40)	(0.42)
(Sh)	(0.21)	(0.76)	(0.36)	(0.91)	(0.54)	(0.90)	(0.86)	(1.60)	(0.63)	(0.84)
λ_{MPU}		-2.37		-2.02		-1.91		-1.87		-1.74
(NW)		(0.80)		(0.81)		(0.56)		(0.73)		(0.53)
(Sh)		(2.07)		(1.81)		(1.22)		(1.56)		(1.06)
R^2	0.81	0.99	0.89	0.99	0.76	0.98	0.84	0.98	0.72	0.98
χ^2_{NW}	[0.02]	[0.85]	[0.10]	[0.76]	[0.01]	[0.67]	[0.04]	[0.63]	[0.00]	[0.62]
χ^2_{Sh}	[0.07]	[0.98]	[0.35]	[0.95]	[0.18]	[0.92]	[0.46]	[0.90]	[0.16]	[0.89]
X	National security		Sovereign debt		US Financial		US Macro		US Real	
λ_X	-3.66	-0.03	-0.80	0.26	-0.89	0.01	-1.69	0.53	-1.20	0.44
(NW)	(1.20)	(0.81)	(0.28)	(0.37)	(0.28)	(0.40)	(0.64)	(0.64)	(0.48)	(0.52)
(Sh)	(4.56)	(1.55)	(0.36)	(0.83)	(0.38)	(0.92)	(1.27)	(1.43)	(0.74)	(1.16)
λ_{MPU}		-1.63		-2.02		-2.05		-1.93		-1.96
(NW)		(0.47)		(0.60)		(0.69)		(0.49)		(0.51)
(Sh)		(0.89)		(1.36)		(1.59)		(1.09)		(1.15)
R^2	0.52	0.98	0.64	0.99	0.81	0.99	0.58	0.99	0.54	1.00
χ^2_{NW}	[0.00]	[0.62]	[0.01]	[0.80]	[0.02]	[0.69]	[0.00]	[0.78]	[0.00]	[0.93]
χ^2_{Sh}	[0.78]	[0.88]	[0.07]	[0.96]	[0.15]	[0.93]	[0.29]	[0.95]	[0.11]	[0.99]

Table A.4. *MPU* **betas of FX momentum under different limits to arbitrage**
The table reports the statistics for the currency momentum portfolios under different limits to arbitrage. I run double sort based on currency's idiosyncratic volatility (or skewness) and realized excess returns over the past 1-, 3- and 6-month horizons to obtain 2×3 portfolios. All portfolios are rebalanced monthly, and the average monthly excess returns (in percentage) are net of transaction costs. The exposures to the risk of US *MPU* are computed from Equation (2.3.1). The standard errors are in parentheses and based on Newey and West (1987) with optimal lag selection following Andrews (1991). The returns and *MPU* betas of high-minus-low portfolios are also reported. The sample period is from January 1985 to August 2017.

	Low idvol		High idvol		Low idskew		High idskew	
	r^e	β_{MPU}	r^e	β_{MPU}	r^e	β_{MPU}	r^e	β_{MPU}
Panel A: Mom 1-1								
L	0.03	0.21	-0.07	0.11	0.04	0.24	-0.08	0.05
	(0.12)	(0.08)	(0.15)	(0.09)	(0.14)	(0.08)	(0.15)	(0.08)
2	0.11	0.01	0.25	-0.03	0.09	0.01	0.21	-0.07
	(0.12)	(0.06)	(0.14)	(0.07)	(0.13)	(0.06)	(0.12)	(0.07)
H	0.23	-0.04	0.33	-0.23	0.29	-0.11	0.29	-0.21
	(0.12)	(0.09)	(0.15)	(0.11)	(0.15)	(0.11)	(0.13)	(0.09)
HML	0.22	-0.25	0.41	-0.36	0.24	-0.35	0.37	-0.26
	(0.13)	(0.15)	(0.15)	(0.17)	(0.15)	(0.17)	(0.14)	(0.15)
Panel B: Mom 3-1								
L	-0.17	0.19	-0.01	0.14	0.04	0.24	-0.05	0.09
	(0.13)	(0.09)	(0.17)	(0.10)	(0.14)	(0.08)	(0.15)	(0.09)
2	0.14	-0.02	0.08	0.03	0.14	-0.03	0.11	0.00
	(0.12)	(0.05)	(0.14)	(0.08)	(0.12)	(0.11)	(0.12)	(0.06)
H	0.28	-0.09	0.42	-0.22	0.23	-0.11	0.47	-0.21
	(0.12)	(0.07)	(0.15)	(0.08)	(0.14)	(0.07)	(0.13)	(0.07)
HML	0.46	-0.28	0.42	-0.36	0.19	-0.35	0.52	-0.31
	(0.14)	(0.14)	(0.15)	(0.15)	(0.13)	(0.14)	(0.14)	(0.14)
Panel C: Mom 6-1								
L	-0.01	0.19	-0.00	0.30	0.16	0.37	-0.03	0.04
	(0.13)	(0.09)	(0.17)	(0.10)	(0.15)	(0.08)	(0.14)	(0.08)
2	0.14	0.01	0.11	-0.09	0.13	-0.10	0.13	-0.07
	(0.12)	(0.05)	(0.14)	(0.06)	(0.12)	(0.07)	(0.12)	(0.06)
H	0.27	-0.08	0.29	-0.21	0.16	-0.11	0.38	-0.25
	(0.12)	(0.09)	(0.16)	(0.11)	(0.13)	(0.09)	(0.14)	(0.09)
HML	0.28	-0.29	0.32	-0.54	0.01	-0.47	0.41	-0.29
	(0.14)	(0.16)	(0.16)	(0.17)	(0.15)	(0.16)	(0.15)	(0.15)

Table A.5. Pricing FX momentum under different limits to arbitrage

The table reports the results of asset pricing test for the two-factor model containing the dollar factor and the MPU risk factor (u_t^{MPU}). The testing assets are momentum portfolios within each group of limits to arbitrage, formed by running double sorts on idiosyncratic volatility (skewness) and realized currency excess returns over the past 1-, 3- and 6-month horizons. The test is done via the Fama-MacBeth regression, where I report the estimated risk prices, cross-sectional OLS R^2, the heteroskedastic and autocorrelation consistent (HAC) standard errors based on Newey and West (1987) with optimal lag selection following Andrews (1991) (NW), and the Shanken-adjusted standard errors of Shanken (1992) (Sh). The p-values of χ^2-test on the null hypothesis that the pricing errors are jointly zero are also reported. Panel B displays the results of test via the GMM estimation, where I report the estimated factor loadings in the SDF model (2.3.5) by using either the identity matrix (GMM1) and the optimal weight matrix (GMM2) in the estimation. The Newey-West standard errors are in parentheses. I also report the the p-values from the overidentifying J-test, and the estimated Hansen-Jaganathan distance with its p-values. The testing assets are the carry, momentum or their joint cross-sectional portfolios. The sample period is from January 1985 to August 2017.

	Low idvol			High idvol			Low idskew			High idskew		
	Panel A: Mom 1-1											
	λ_{DOL}	λ_{MPU}	R^2	λ_{DOL}	λ_{MPU}	R^2	λ_{DOL}	λ_{MPU}	R^2	λ_{DOL}	λ_{MPU}	R^2
	0.17	-0.69	0.63	0.09	-1.06	0.79	0.17	-0.63	0.80	0.03	-1.41	0.88
(NW)	(0.12)	(0.45)		(0.11)	(0.40)		(0.11)	(0.39)		(0.12)	(0.54)	
(Sh)	(0.13)	(0.54)		(0.12)	(0.58)		(0.12)	(0.46)		(0.15)	(0.93)	
χ^2_{NW}	2.97			2.22			1.01			2.32		
	(0.08)			(0.14)			(0.31)			(0.13)		
χ^2_{Sh}	2.00			1.05			0.72			0.78		
	(0.16)			(0.31)			(0.40)			(0.38)		
	Panel B: Mom 3-1											
	λ_{DOL}	λ_{MPU}	R^2	λ_{DOL}	λ_{MPU}	R^2	λ_{DOL}	λ_{MPU}	R^2	λ_{DOL}	λ_{MPU}	R^2
	0.14	-1.60	0.98	0.14	-1.17	1.00	0.16	-0.54	0.96	0.11	-1.75	0.99
(NW)	(0.12)	(0.47)		(0.11)	(0.39)		(0.11)	(0.37)		(0.11)	(0.41)	
(Sh)	(0.14)	(0.87)		(0.12)	(0.59)		(0.12)	(0.42)		(0.13)	(0.83)	
χ^2_{NW}	0.76			0.01			0.16			0.17		
	(0.38)			(0.90)			(0.69)			(0.68)		
χ^2_{Sh}	0.21			0.01			0.12			0.04		
	(0.64)			(0.94)			(0.72)			(0.84)		
	Panel C: Mom 6-1											
	λ_{DOL}	λ_{MPU}	R^2	λ_{DOL}	λ_{MPU}	R^2	λ_{DOL}	λ_{MPU}	R^2	λ_{DOL}	λ_{MPU}	R^2
	0.21	-0.92	0.92	0.12	-0.49	0.81	0.15	-0.01	-0.27	0.02	-1.46	1.00
(NW)	(0.12)	(0.50)		(0.11)	(0.29)		(0.11)	(0.27)		(0.12)	(0.50)	
(Sh)	(0.13)	(0.68)		(0.11)	(0.33)		(0.11)	(0.27)		(0.15)	(0.88)	
χ^2_{NW}	1.05			1.21			0.26			0.00		
	(0.31)			(0.27)			(0.61)			(0.95)		
χ^2_{Sh}	0.56			0.97			0.26			0.00		
	(0.45)			(0.32)			(0.61)			(0.97)		

Table A.6. Asset pricing performance with other *MPU* shocks

The table reports the results of asset pricing test for the two-factor model containing the dollar factor and the US *MPU* risk, which is obtained by using different controls on the right-hand side of Equation (2.2.2). Panel A to C reports the results of using simple change in BBD *MPU* index (no controls), using BBD uncertainty index of Taxes and Fiscal & spending policy as controls, and using all category-specific BBD policy uncertainty indexes as controls, respectively. In each panel, I first report the estimated *MPU* betas of carry and momentum portfolios, their Newey-West standard errors and the p-values of two types of monotonic relation (MR) test. Then I display the results of asset pricing test via the Fama-MacBeth regression, where I report the estimated risk prices, cross-sectional OLS R^2, the heteroskedastic and autocorrelation consistent (HAC) standard errors based on Newey and West (1987) with optimal lag selection following Andrews (1991) (NW), and the Shanken-adjusted standard errors of Shanken (1992) (Sh). The p-values of χ^2-test on the null hypothesis that the pricing errors are jointly zero are also reported. The testing assets are the carry, momentum or their joint cross-sectional portfolios. The sample period is from January 1985 to August 2017.

Panel A: ΔMPU_t							
	L	2	3	4	H	HML	MR
β^C_{MPU}	0.23	0.06	0.01	-0.00	-0.30	-0.52	1.00
	(0.07)	(0.05)	(0.04)	(0.05)	(0.10)	(0.15)	(0.98)
β^M_{MPU}	0.01	0.10	-0.01	0.02	-0.11	-0.13	1.00
	(0.11)	(0.06)	(0.07)	(0.05)	(0.09)	(0.19)	(0.93)
λ^C_{MPU}	-0.99	R^2	0.84	χ^2_{NW}	[0.09]		
(NW)	(0.32)			χ^2_{Sh}	[0.35]		
(Sh)	(0.45)						
λ^M_{MPU}	-2.07	R^2	0.59	χ^2_{NW}	[0.05]		
(NW)	(0.60)			χ^2_{Sh}	[0.68]		
(Sh)	(1.39)						
λ^{C+M}_{MPU}	-1.14	R^2	0.66	χ^2_{NW}	[0.05]		
(NW)	(0.31)			χ^2_{Sh}	[0.56]		
(Sh)	(0.47)						
Panel B: using tax and fiscal policy uncertainties as controls							
	L	2	3	4	H	HML	MR
β^C_{MPU}	0.16	0.08	-0.01	-0.02	-0.21	-0.37	[1.00]
	(0.07)	(0.05)	(0.04)	(0.06)	(0.09)	(0.14)	(0.98)
β^M_{MPU}	0.06	0.13	-0.00	-0.01	-0.16	-0.22	[1.00]
	(0.09)	(0.06)	(0.06)	(0.05)	(0.09)	(0.16)	(0.94)
λ^C_{MPU}	-1.37	R^2	0.86	χ^2_{NW}	[0.12]		
(NW)	(0.42)			χ^2_{Sh}	[0.56]		
(Sh)	(0.71)						
λ^M_{MPU}	-1.70	R^2	0.80	χ^2_{NW}	[0.30]		
(NW)	(0.45)			χ^2_{Sh}	[0.81]		
(Sh)	(0.89)						
λ^{C+M}_{MPU}	-1.48	R^2	0.82	χ^2_{NW}	[0.05]		
(NW)	(0.36)			χ^2_{Sh}	[0.78]		
(Sh)	(0.65)						
Panel C: using all category-specific policy uncertainties as controls							
	L	2	3	4	H	HML	MR
β^C_{MPU}	0.18	0.06	-0.04	-0.05	-0.15	-0.32	[1.00]
	(0.07)	(0.05)	(0.04)	(0.06)	(0.09)	(0.13)	(0.99)
β^M_{MPU}	0.21	0.11	-0.04	-0.07	-0.19	-0.39	[1.00]
	(0.09)	(0.06)	(0.06)	(0.05)	(0.09)	(0.17)	(0.94)
λ^C_{MPU}	-1.68	R^2	0.98	χ^2_{NW}	[0.81]		
(NW)	(0.47)			χ^2_{Sh}	[0.97]		
(Sh)	(0.92)						
λ^M_{MPU}	-1.30	R^2	0.99	χ^2_{NW}	[0.96]		
(NW)	(0.35)			χ^2_{Sh}	[0.99]		
(Sh)	(0.57)						
λ^{C+M}_{MPU}	-1.44	R^2	0.97	χ^2_{NW}	[0.02]		
(NW)	(0.33)			χ^2_{Sh}	[0.64]		
(Sh)	(0.57)						

Figure A.1. Other proxies for the US monetary policy uncertainty

The figure plots the realized variance of US Treasury bond yields, computed from daily data with maturities of 1-year and 10-year. The sample ranges from January 1985 to August 2017.

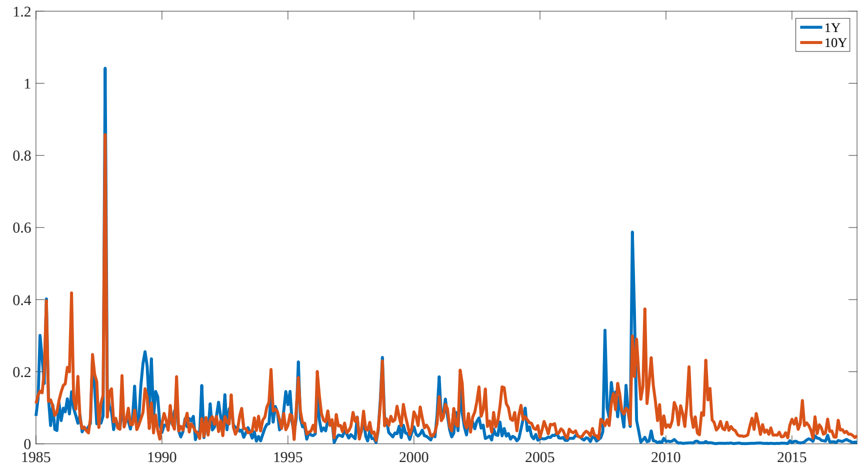
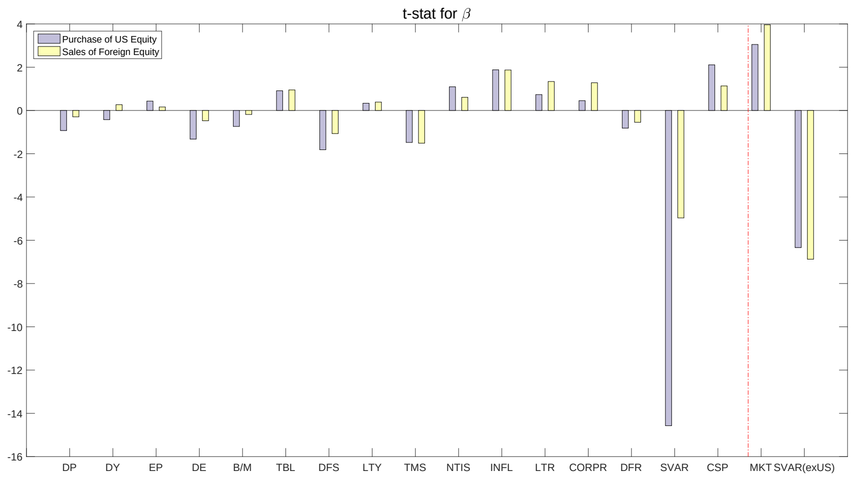


Figure A.2. Impact on the intermediary sector (month-to-month flow growth)

The figure plots the t-statistics for γ and β estimates from Equation (2.4.8), when the dependent variables are the month-to-month log changes in equity flows. The control variables include 16 predictors from Welch and Goyal (2007), the international stock return predictor from Rapach et al. (2013), and the return variance constructed from stock markets outside the US. The red vertical line separates the states governing the demand for US equity (to the left) and demand for foreign equity (to the right). The sample period is from January 1985 to August 2017.



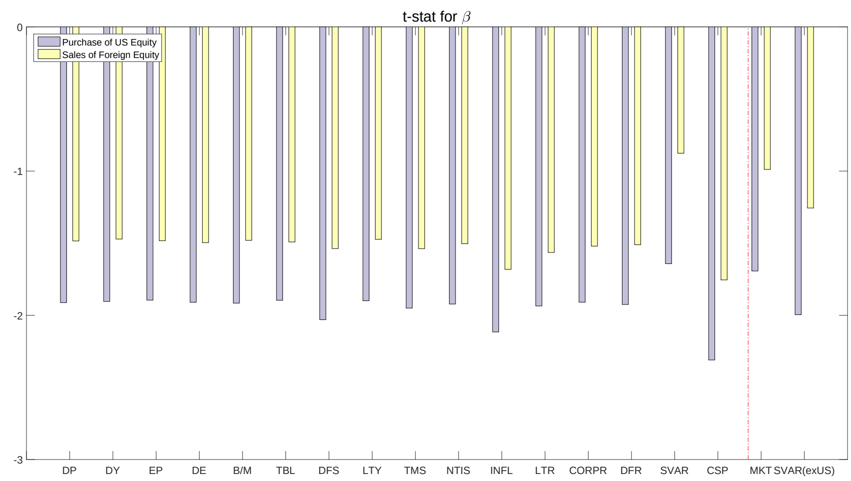
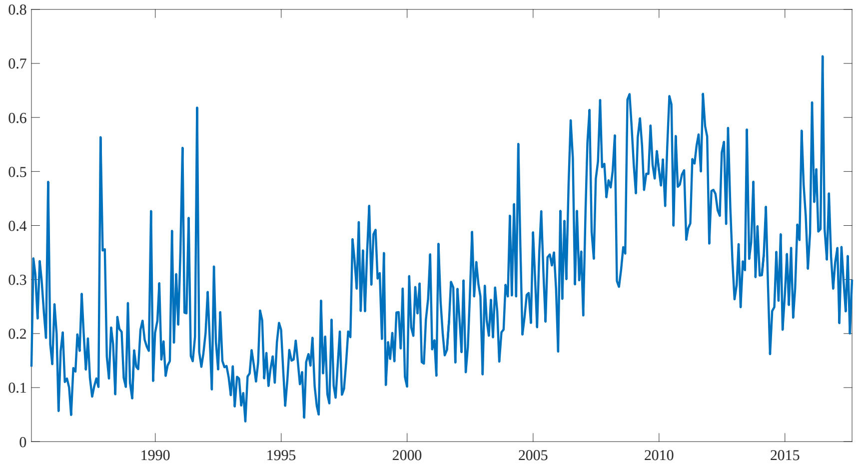


Figure A.3. Time-series plot of global equity correlation

The figure plots the replicated series of global equity correlation of Bae and Elkamhi (2017). The sample period is from January 1985 to August 2017.



5.2 Appendix to Chapter 2

Table A.7. Alternative measures for *NAC*

This table reports the results of the predictive regression:

$$r^{CSIP}_{t+1:t+h} = a + b_{NAC}NAC_t + \varepsilon_{t+1:t+h},$$

where *NAC* is computed as the time-varying correlation (i) between inflation and ambiguity over a 20-quarter rolling window; (ii) between shocks to inflation and ambiguity over a 12-quarter rolling window; (iii) between shocks to inflation and ambiguity over a 16-quarter rolling window. The three risk premium measures are in percentage and include the high-minus-low return spreads of value-weighted (VW) and equal-weighted (EW) inflation beta sorted portfolios, and the stock-level risk price estimates (Stock) from the cross-sectional regression. The monthly returns within the quarter are compounded to quarterly frequency, and the forecasting horizons cover from one-quarter to four-quarter. IVX-p denotes the p-value of the IVX Wald test of Kostakis et al. (2014) on testing $H_0 : b_{NAC} = 0$ against $H_1 : b_{NAC} \neq 0$. R^2_{IS} is for the in-sample regression, and R^2_{OOS} measures the out-of-sample relative performance of forecasting compared with the historical average model. The significance of R^2_{OOS} is based on the MSPE-adjusted statistic of Clark and West (2007). *, **, *** denote significance at 10%, 5% and 1% level. Data sample ranges from Q3 of 1986 to Q4 of 2017.

Horizon		Level				3-year window				4-year window			
		b_{NAC}	p	R^2_{IS}	R^2_{OOS}	b_{NAC}	p	R^2_{IS}	R^2_{OOS}	b_{NAC}	p	R^2_{IS}	R^2_{OOS}
	VW	-5.88	0.01	4.32	3.45***	-3.20	0.14	1.59	0.75*	-4.24	0.08	2.13	1.16*
$h=1$	EW	-3.73	0.02	3.74	2.74**	-3.95	0.01	5.08	4.21***	-3.93	0.02	3.84	3.04**
	Stock	-4.04	0.01	5.62	3.80**	-3.47	0.01	5.13	3.67***	-3.38	0.03	3.70	2.14*
	VW	-5.26	0.02	6.89	3.99***	-2.74	0.18	2.34	2.11*	-3.75	0.11	3.31	2.07**
$h=2$	EW	-3.69	0.02	6.65	1.90**	-4.12	0.00	9.92	7.98***	-3.67	0.02	6.03	1.91*
	Stock	-4.22	0.00	13.46	3.86**	-3.71	0.01	12.67	7.21***	-3.33	0.03	7.79	0.62
	VW	-4.98	0.02	8.18	-0.42	-3.17	0.11	4.12	3.86**	-4.07	0.07	5.16	3.15**
$h=3$	EW	-3.25	0.04	6.70	-5.32	-4.11	0.00	13.07	6.27**	-3.31	0.03	6.49	-1.67
	Stock	-3.42	0.01	11.52	-5.12	-3.27	0.01	12.93	3.87**	-2.72	0.06	6.84	-1.25
	VW	-4.20	0.05	7.11	-1.28	-3.23	0.10	5.24	5.54**	-3.77	0.09	5.42	5.81**
$h=4$	EW	-2.78	0.07	6.08	-5.92	-3.94	0.00	14.93	4.75**	-2.99	0.05	6.59	1.38
	Stock	-2.86	0.03	11.46	-5.32	-2.98	0.02	15.29	2.88*	-2.44	0.09	7.87	0.91

Table A.8. Inflation betas estimated under various controls

This table reports the results of the predictive regression:

$$r^{CSIP}_{t+1:t+h} = a + b_{NAC}\mathbb{I}_{NAC_t>0} + \varepsilon_{t+1:t+h},$$

where NAC is computed as the time-varying correlation between shocks to inflation and ambiguity over a 20-quarter rolling window. The three risk premium measures are in percentage and include the high-minus-low return spreads of value-weighted (VW) and equal-weighted (EW) inflation beta sorted portfolios, and the stock-level risk price estimates (Stock) from the cross-sectional regression. The inflation betas of stock i is estimated by controlling for the Fama-French three-factor, Carhart four-factor and Fama-French five-factor. The monthly returns within the quarter are compounded to quarterly frequency, and the forecasting horizons cover from one-quarter to four-quarter. IVX-p denotes the p-value of the IVX Wald test of Kostakis et al. (2014) on testing $H_0: b_{NAC} = 0$ against $H_1: b_{NAC} \neq 0$. R^2_{IS} is for the in-sample regression, and R^2_{OOS} measures the out-of-sample relative performance of forecasting compared with the historical average model. The significance of R^2_{OOS} is based on the MSPE-adjusted statistic of Clark and West (2007). *, **, *** denote significance at 10%, 5% and 1% level. Data sample ranges from Q3 of 1986 to Q4 of 2017.

Horizon		FF-3F				Carhart-4F				FF-5F			
		b_{NAC}	p	R^2_{IS}	R^2_{OOS}	b_{NAC}	p	R^2_{IS}	R^2_{OOS}	b_{NAC}	p	R^2_{IS}	R^2_{OOS}
	VW	-5.01	0.01	6.01	4.76***	-4.18	0.03	3.86	2.33**	-5.12	0.00	7.12	5.86***
$h=1$	EW	-3.69	0.00	7.84	6.52***	-3.60	0.00	8.95	7.41***	-3.81	0.00	8.19	6.92***
	Stock	-2.77	0.02	5.59	4.53***	-2.77	0.02	5.63	4.58***	-3.23	0.02	5.28	4.22***
	VW	-4.23	0.03	7.51	1.07	-2.53	0.11	3.95	-1.35	-4.30	0.01	8.41	2.67*
$h=2$	EW	-3.32	0.01	10.95	3.80**	-2.62	0.00	13.22	7.70***	-3.48	0.01	11.00	2.50*
	Stock	-3.08	0.02	10.86	4.31***	-2.34	0.02	11.13	4.87**	-3.03	0.03	8.98	2.43*
	VW	-3.79	0.05	8.56	-0.70	-2.46	0.20	3.89	-2.86	-3.43	0.02	10.05	1.75
$h=3$	EW	-3.08	0.01	12.27	2.58**	-2.66	0.00	14.81	6.86***	-3.55	0.01	11.11	0.21
	Stock	-2.53	0.04	10.63	1.68*	-2.50	0.04	10.98	2.37**	-2.72	0.06	8.13	-0.20
	VW	-3.43	0.05	10.71	4.89***	-2.10	0.22	4.50	-1.28	-3.55	0.02	13.23	5.27**
$h=4$	EW	-2.61	0.02	13.62	9.58***	-3.02	0.00	15.92	13.63***	-3.22	0.02	11.67	5.22**
	Stock	-2.29	0.07	10.98	6.38***	-2.56	0.07	11.37	7.57***	-2.43	0.12	7.57	4.42*

Table A.9. Predictive power when *NRC* is obtained from monthly data

This table reports the results of the bivariate predictive regression:

$$r^{CSIP}_{t+1:t+h} = a + b_{NAC}\mathbb{I}_{NAC_t>0} + b_{NRC}NRC_t + \varepsilon_{t+1:t+h},$$

where *NAC* is computed as the time-varying correlation between shocks to inflation and ambiguity over a 20-quarter rolling window, and *NRC* is estimated from monthly data of inflation and growth according to Equation (3.3.3) with one-year forecasting horizon. NRC_1 and NRC_2 denote the aggregation methods that take end-of-quarter value, and the within-quarter averages. The three risk premium measures are in percentage and include the high-minus-low return spreads of value-weighted (VW) and equal-weighted (EW) inflation beta sorted portfolios, and the stock-level risk price estimates (Stock) from the cross-sectional regression. The monthly returns within the quarter are compounded to quarterly frequency, and the forecasting horizons cover from one-quarter to four-quarter. The t-statistics of predictive coefficients are in parentheses and based on the standard errors of Newey and West (1987) with optimal lag selection following Andrews (1991). Data sample ranges from Q3 of 1986 to Q4 of 2017.

	VW		EW		Stock	
Panel A: $h=1$						
NAC	-4.64	-3.42	-2.74	-4.64	-3.35	-2.67
	(-1.75)	(-2.26)	(-2.21)	(-1.78)	(-2.28)	(-2.22)
NRC_1	2.38		-5.31		-1.17	
	(0.25)		(-1.09)		(-0.30)	
NRC_2		2.36		-4.60		-0.52
		(0.26)		(-1.00)		(-0.14)
Panel B: $h=2$						
NAC	-3.29	-2.97	-2.35	-3.33	-2.94	-2.31
	(-1.58)	(-2.55)	(-2.46)	(-1.60)	(-2.58)	(-2.49)
NRC_1	6.71		-3.30		0.36	
	(0.84)		(-0.84)		(0.11)	
NRC_2		6.36		-2.93		0.72
		(0.79)		(-0.79)		(0.24)
Panel C: $h=3$						
NAC	-2.98	-2.69	-1.83	-3.13	-2.71	-1.84
	(-1.60)	(-2.65)	(-2.62)	(-1.66)	(-2.70)	(-2.67)
NRC_1	8.18		-1.54		2.23	
	(1.09)		(-0.44)		(0.77)	
NRC_2		6.72		-1.73		2.17
		(0.87)		(-0.50)		(0.74)
Panel D: $h=4$						
NAC	-2.64	-2.33	-1.37	-2.79	-2.35	-1.38
	(-1.48)	(-2.49)	(-1.96)	(-1.54)	(-2.54)	(-1.98)
NRC_1	8.44		-0.43		3.38	
	(1.09)		(-0.12)		(1.06)	
NRC_2		6.99		-0.61		3.26
		(0.87)		(-0.17)		(1.00)

Table A.10. Forecasting inflation risk premium with various controls

This table reports the results of the bivariate predictive regression:

$$r^{CSIP}_{t+1:t+h} = a + b_{NAC}\mathbb{I}_{NAC_t>0} + b_X X_t + \varepsilon_{t+1:t+h},$$

where *NAC* is computed as the time-varying correlation between shocks to inflation and ambiguity over a 20-quarter rolling window, and *X* is the aggregate stock market predictors as surveyed by Welch and Goyal (2007). The three risk premium measures are in percentage and include the high-minus-low return spreads of value-weighted (VW) and equal-weighted (EW) inflation beta sorted portfolios, and the stock-level risk price estimates (Stock) from the cross-sectional regression. The monthly returns within the quarter are compounded to quarterly frequency, and the forecasting horizons cover from one-quarter to four-quarter. The t-statistics of predictive coefficients are in parentheses and based on the standard errors of Newey and West (1987) with optimal lag selection following Andrews (1991). Data sample ranges from Q3 of 1986 to Q4 of 2016.

Variable	$h=1$		$h=2$		$h=3$		$h=4$	
	NAC	*X*	*NAC*	*X*	*NAC*	*X*	*NAC*	*X*
DP	-4.58	1.35	-3.71	1.28	-3.60	1.31	-3.41	1.31
	(-2.23)	(0.95)	(-2.23)	(0.98)	(-2.33)	(1.04)	(-2.31)	(1.09)
DY	-4.64	1.29	-3.75	1.42	-3.65	1.42	-3.46	1.38
	(-2.28)	(0.93)	(-2.26)	(1.05)	(-2.37)	(1.11)	(-2.35)	(1.16)
EP	-4.67	0.37	-3.78	0.43	-3.66	0.67	-3.46	0.79
	(-2.26)	(0.31)	(-2.26)	(0.43)	(-2.34)	(0.74)	(-2.33)	(1.01)
DE	-4.72	0.45	-3.84	0.36	-3.73	0.20	-3.54	0.10
	(-2.32)	(0.75)	(-2.30)	(0.61)	(-2.35)	(0.35)	(-2.33)	(0.19)
BM	-4.49	0.81	-3.46	1.35	-3.35	1.37	-3.16	1.35
	(-2.02)	(0.30)	(-1.93)	(0.54)	(-2.11)	(0.60)	(-2.10)	(0.62)
TBL	-4.86	0.81	-4.03	0.95	-3.95	0.95	-3.78	0.94
	(-2.48)	(1.04)	(-2.55)	(1.23)	(-2.66)	(1.26)	(-2.66)	(1.31)
DFS	-4.73	-0.04	-3.58	0.41	-3.47	0.41	-3.30	0.38
	(-2.29)	(-0.05)	(-2.10)	(0.60)	(-2.15)	(0.63)	(-2.13)	(0.68)
LTY	-4.73	0.16	-3.87	0.34	-3.79	0.39	-3.63	0.46
	(-2.33)	(0.24)	(-2.35)	(0.55)	(-2.43)	(0.68)	(-2.42)	(0.85)
TMS	-4.95	-1.07	-4.06	-1.07	-3.94	-1.01	-3.73	-0.92
	(-2.62)	(-1.08)	(-2.67)	(-1.08)	(-2.74)	(-1.03)	(-2.67)	(-1.02)
CAY	-4.75	0.95	-3.92	0.96	-3.87	0.99	-3.76	1.17
	(-2.37)	(1.75)	(-2.43)	(1.83)	(-2.55)	(1.98)	(-2.63)	(2.44)
NTIS	-4.59	-0.18	-3.64	-0.26	-3.58	-0.20	-3.34	-0.27
	(-2.10)	(-0.23)	(-2.04)	(-0.40)	(-2.12)	(-0.38)	(-2.11)	(-0.58)
INFL	-4.76	-0.35	-3.88	-0.45	-3.79	-0.44	-3.61	-0.49
	(-2.31)	(-0.63)	(-2.30)	(-0.83)	(-2.37)	(-0.93)	(-2.36)	(-1.32)
LTR	-4.83	1.57	-3.87	0.53	-3.75	0.33	-3.56	0.33
	(-2.38)	(1.59)	(-2.33)	(0.92)	(-2.38)	(0.71)	(-2.35)	(0.93)
CORPR	-4.62	1.36	-3.81	0.22	-3.71	0.22	-3.52	0.17
	(-2.29)	(1.95)	(-2.30)	(0.51)	(-2.34)	(0.59)	-(2.30)	(0.60)
SVAR	-4.65	0.17	-3.81	0.04	-3.70	0.08	-3.50	0.10
	(-2.25)	(0.40)	(-2.25)	(0.08)	(-2.26)	(0.14)	(-2.21)	(0.23)
IK	-4.79	0.11	-3.76	-0.09	-3.63	-0.14	-3.42	-0.16
	(-2.26)	(0.09)	(-2.17)	(-0.07)	(-2.42)	(-0.11)	(-2.33)	(-0.14)

Table A.11. Alternative risk factors

This table reports the results of the panel regression by pooling 3 aggregate-level measures for the cross-sectional inflation risk premium:

$$r^i_{t+1:t+h} = \alpha_0 + \beta_{NAC} NAC_t + \beta_X X_t + \varepsilon^i_{t+1:t+h},$$

where X_t denotes the control variables that are either *NRC* or the forecast dispersion. Returns are in percentages. Panel A replaces the original risk factor by the factor-mimicking portfolio returns, and Panel B replaces the original risk factor by the raw inflation series. The forecasting horizon ranges from one-quarter to four-quarter. The t-statistics are in parentheses and based on the asymptotic Driscoll and Kraay (1998) standard errors with lag h. Data sample ranges from Q3 of 1986 to Q4 of 2017.

	h=1			h=2			h=3			h=4		
Panel A: Factor-mimicking portfolio												
NAC	-0.83	-0.72	-0.93	-0.79	-0.64	-0.94	-0.73	-0.58	-1.01	-0.66	-0.53	-0.86
	(-1.44)	(-1.20)	(-1.54)	(-1.43)	(-1.19)	(-1.64)	(-1.40)	(-1.17)	(-1.90)	(-1.36)	(-1.12)	(-1.83)
NRC		0.26			0.38			0.38			0.31	
		(0.31)			(0.51)			(0.55)			(0.46)	
Disp			-0.27			-0.40			-0.74			-0.53
			(-0.37)			(-0.79)			(-1.67)			(-1.32)
$R^2(\%)$	0.79	0.86	0.86	1.40	1.67	1.71	1.73	2.13	3.22	1.83	2.17	2.86
Nobs	375	375	375	372	372	372	369	369	369	366	366	366
Panel B: Raw inflation												
NAC	-1.08	-0.88	-0.93	-1.06	-0.82	-0.87	-0.93	-0.69	-0.80	-0.80	-0.57	-0.65
	(-2.78)	(-1.82)	(-2.15)	(-2.71)	(-1.72)	(-2.23)	(-2.49)	(-1.52)	(-2.00)	(-2.26)	(-1.26)	(-1.70)
NRC		0.49			0.61			0.61			0.58	
		(0.86)			(1.16)			(1.18)			(1.05)	
Disp			0.40			0.50			0.35			0.41
			(0.73)			(1.03)			(0.81)			(0.99)
$R^2(\%)$	2.34	2.75	2.61	4.55	5.82	5.40	4.75	6.48	5.33	4.50	6.48	5.49
Nobs	375	375	375	372	372	372	369	369	369	366	366	366

Figure A.4. Nominal-Ambiguity Correlation obtained under different methods

This figure plots the nominal-ambiguity correlation (NAC) estimated via the time-varying correlations (i) between inflation and ambiguity over a 20-quarter rolling window; (ii) between shocks to inflation and ambiguity over a 12-quarter rolling window; (iii) between shocks to inflation and ambiguity over a 16-quarter rolling window. Data sample ranges from Q3 of 1986 to Q4 of 2017.

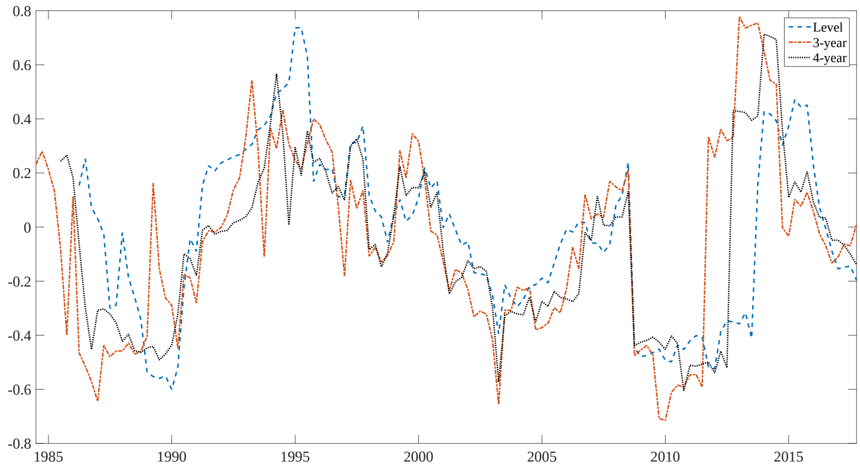
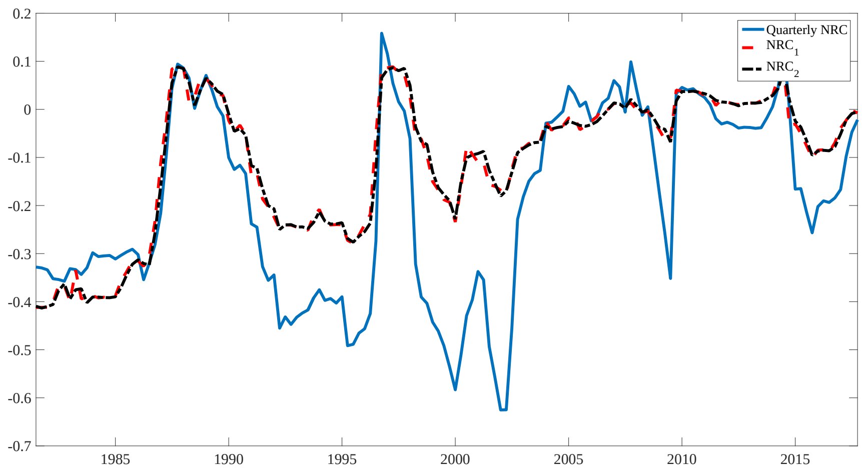


Figure A.5. Nominal-real covariance obtained under different methods

This figure plots the nominal-real covariance (NRC) estimated using quarterly and monthly data. The quarterly estimates are as in the benchmark setting. The NRC is estimated from monthly data of inflation and growth according to Equation (3.3.3) with one-year forecasting horizon. NRC_1 and NRC_2 denote the aggregation methods that take end-of-quarter value, and the within-quarter averages. Data sample ranges from Q3 of 1986 to Q4 of 2017.



5.3 Appendix to Chapter 3

5.3.1 Details of Predictors

We obtain data of most predictors from Amit Goyal's website. The investor sentiment data is from Jeffery Wurgler's website. The details of 14 predictors are listed below:

- Long term return (LTR): return on the long term government bond
- Inflation (INFL): calculated from CPI for all urban consumers, lagged for two months to wait for the CPI releases
- Long term yield (LTY): yield of long term government bond
- Stock variance (SVAR)constructed from the sum of squared daily returns of S&P 500
- Dividend-payout ratio (DE):difference between the log dividend and the log earnings
- Default yield spread (DFY): difference between the yields on BAA- and AAA-rated corporate bond
- Treasury bill rate (TBL): secondary market three-month Treasury bill rate
- Dividend yield (DY): difference between the log dividend and the log of lagged price
- Earnings price ratio (EP):difference between the log earnings and the log price
- Term spread (TMS): difference between long-term yield and Treasury bill rate
- Book-to-market ratio (BM): ratio of book value to market value for DJIA
- Dividend price ratio (DP): difference between the log dividend and log price

- Net equity expansion (NTIS): ratio of 12-month moving sums of net issues by NYSE listed stocks to end-of-year total market capitalization
- Investor sentiment (IS): constructed from the first principal component of five standardized sentiment proxies, where each of the proxies has first been orthogonalized with respect to a set of six macroeconomic indicators

5.3.2 Details of 30 industry portfolios

- Food: Food Products
- Beer: Beer and Liquor
- Smoke: Tobacco Products
- Games: Recreation
- Books: Printing and Publishing
- Hshld: Consumer Goods
- Clths: Apparel
- Hlth: Healthcare, Medical Equipment, Pharmaceutical Products
- Chems: Chemicals
- Txtls: Textiles
- Cnstr: Construction and Construction Materials
- Steel: Steel Works Etc
- FabPr: Fabricated Products and Machinery
- ElcEq: Electrical Equipment
- Autos: Automobiles and Trucks
- Carry: Aircraft, ships, and railroad equipment

- Mines: Precious Metals, Non-Metallic, and Industrial Metal Mining
- Coal: Coal
- Oil: Petroleum and Natural Gas
- Util: Utilities
- Telcm: Communication
- Servs: Personal and Business Services
- BusEq: Business Equipment
- Paper: Business Supplies and Shipping Containers
- Trans: Transportation
- Whlsl: Wholesale
- Rtail: Retail
- Meals: Restaraunts, Hotels, Motels
- Fin: Banking, Insurance, Real Estate, Trading
- Other: Everything Else

5.3.3 Proof of Propositions

This appendix provides the derivation of risk-neutral one period ahead expected variance in affine model. First notice that:

$$E_t^Q[\sigma_{t+1}^2] = E_t[M_{t+1}\sigma_{t+1}^2]/E_t[M_{t+1}] \tag{A.1}$$

We derive the expression for the nominator as follows:

$$
\begin{aligned}
E_t[M_{t+1}\sigma_{t+1}^2] &= E_t[\exp(-r_t - \frac{1}{2}\lambda_t^{'}\lambda_t - \lambda_t^{'}\varepsilon_{t+1})(a+b'Z_{t+1})'(a+b'Z_{t+1})] \\
&= \exp(-r_t - \frac{1}{2}\lambda_t^{'}\lambda_t)E_t[\exp(-\lambda_t^{'}\varepsilon_{t+1})(a+b'(\mu+\Phi Z_t+\Sigma\varepsilon_{t+1}))'(a+b'(\mu+\Phi Z_t+\Sigma\varepsilon_{t+1} \\
&= \exp(-r_t - \frac{1}{2}\lambda_t^{'}\lambda_t)E_t[\exp(-\lambda_t^{'}\varepsilon_{t+1})(\varepsilon_{t+1}^{'}\Sigma' bb'\Sigma\varepsilon_{t+1} + 2(a+b'(\mu+\Phi X_t)))'b'\Sigma\varepsilon_{t+1} \\
&+ (a+b'(\mu+\Phi Z_t))'(a+b'(\mu+\Phi Z_t)))]
\end{aligned}
$$

Thus we only need to calculate three terms involved in the last conditional expectation.

The first part is the quadratic term:

$$
\begin{aligned}
E_t[\exp(-\lambda_t^{'}\varepsilon_{t+1})\varepsilon_{t+1}^{'}\Sigma' bb'\Sigma\varepsilon_{t+1}] &= \int \exp(-\frac{1}{2}\varepsilon_{t+1}^{'}\varepsilon_{t+1} - \lambda_t^{'}\varepsilon_{t+1})\varepsilon_{t+1}^{'}\Sigma' bb'\Sigma\varepsilon_{t+1}d\varepsilon_{t+1} \\
&= \exp(\frac{1}{2}\lambda_t^{'}\lambda_t)\int \exp(-\frac{1}{2}(\varepsilon_{t+1}+\lambda_t)^{'}(\varepsilon_{t+1}+\lambda_t))\varepsilon_{t+1}^{'}\Sigma' bb'\Sigma\varepsilon_{t+1}d\varepsilon_{t+1}
\end{aligned}
$$

The integral actually computes $E_t[\varepsilon_{t+1}^{'}\Sigma' bb'\Sigma\varepsilon_{t+1}]$, whereas $\varepsilon_{t+1}|F_t \sim N(-\lambda_t, I)$, thus its expression is reduced to:

$$
E_t[\varepsilon_{t+1}^{'}\Sigma' bb'\Sigma\varepsilon_{t+1}] = E_t[tr(b'\Sigma\varepsilon_{t+1}\varepsilon_{t+1}^{'}\Sigma' b)] = tr(E_t[b'\Sigma\varepsilon_{t+1}\varepsilon_{t+1}^{'}\Sigma' b]) = tr(b'\Sigma\Sigma' b + b'\Sigma\lambda_t\lambda_t^{'}\Sigma' b) \tag{A.2}
$$

So the first part will be:

$$
E_t[\exp(-\lambda_t^{'}\varepsilon_{t+1})(\varepsilon_{t+1}^{'}\Sigma' bb'\Sigma\varepsilon_{t+1})] = \exp(\frac{1}{2}\lambda_t^{'}\lambda_t)tr(b'\Sigma\Sigma' b + b'\Sigma\lambda_t\lambda_t^{'}\Sigma' b)
$$

Then the second part can be obtained similarly:

$$
E_t[\exp(-\lambda_t^{'}\varepsilon_{t+1})(a+b'(\mu+\Phi Z_t))'b'\Sigma\varepsilon_{t+1}] = -\exp(\frac{1}{2}\lambda_t^{'}\lambda_t))(a+b'(\mu+\Phi Z_t))'b'\Sigma\lambda_t
$$

The last part is constant term so it remains unchanged after taking expectations.

After using the fact that $E_t[M_{t+1}] = \exp(-r_t)$, the proof is done.

As for the second proposition, denote $\theta = \frac{1-\gamma}{1-\frac{1}{\psi}}$, $G = (\frac{C}{((1-\gamma)J)^{\frac{1}{1-\gamma}}})^{1-\frac{1}{\psi}}$, then the aggregator can be written as:

$$f(C,J) = \beta\theta J(G-1) \tag{A.3}$$

The partial derivative is:

$$f_J = (\theta-1)\beta G - \beta\theta \tag{A.4}$$

$$f_C = \beta\frac{G}{C}(1-\gamma)J \tag{A.5}$$

Conjecture the value function has the form:

$$J(W,y) = \exp(A_0 + A_1 y)\frac{W^{1-\gamma}}{1-\gamma} \tag{A.6}$$

Using the envelope condition $f_C = J_W$, we obtain

$$\beta G = \frac{C_t}{W_t} \tag{A.7}$$

$$C = J_W^{-\psi}((1-\gamma)J)^{\frac{1-\gamma\psi}{1-\gamma}}\beta^{\psi} \tag{A.8}$$

Combine (A.6) and (A.8), we can express the value function as function of consumption:

$$J(C,y) = \beta^{-\psi(1-\gamma)}\exp(\psi(A_0 + A_1 y))\frac{C^{1-\gamma}}{1-\gamma} \tag{A.9}$$

Then (A.8) and (A.9) together will give the consumption-wealth ratio:

$$\frac{C}{W} = \beta^{\psi}\exp[(A_0 + A_1 y)\frac{1-\psi}{1-\gamma}] \tag{A.10}$$

We use the log-linear approximation as proposed in Chacko and Viceira (2005) and equation (A.7):

$$\frac{C_t}{W_t} \approx g_1 - g_1 \log g_1 + g_1 \log(\beta G) \tag{A.11}$$

where g_1 is the steady state consumption-wealth ratio.

On the other hand, the aggregator under such log-linearization is:

$$f = \theta J(\beta G - \beta) \approx \theta J(g_1 - \beta - g_1 \log g_1 + g_1 \log \beta + g_1 \log G) = \theta J[g_1 \frac{1-\psi}{1-\gamma}(A_0 + A_1 y) + \xi] \tag{A.12}$$

where $\xi = g_1 - g_1 \log g_1 + g_1 \psi \log \beta - \beta$

Now we show how to find A_0 and A_1 in the conjectured solution (A.9). The HJB equation at optimal consumption is:

$$f(C,J) + C\mu J_C + \frac{1}{2} y C^2 J_{CC} + (\sigma^2 - 2\kappa y) J_y + 2\sigma^2 y J_{yy} + 2\sigma c y F L' J_{Cy} = 0 \tag{A.13}$$

The solution (A.9) has the property:

$$J_C = \frac{J(1-\gamma)}{C} \tag{A.14}$$

$$J_{CC} = \frac{J(1-\gamma)(-\gamma)}{C^2} \tag{A.15}$$

$$J_y = \psi A_1 J \tag{A.16}$$

$$J_{Cy} = \frac{\psi A_1 J (1-\gamma)}{C} \tag{A.17}$$

$$J_{yy} = \psi^2 A_1^2 J \tag{A.18}$$

Replace into (A.13), and use the log-linear approximation of $f(C,J)$, we obtain:

$$\theta J[g_1 \frac{1-\psi}{1-\gamma}(A_0 + A_1 y) + \xi] + J(1-\gamma)\mu + \frac{1}{2}\gamma(\gamma - 1) J y + 2\sigma^2 \psi^2 A_1^2 y J + 2\sigma \psi A_1 J (1-\gamma) y F L' = 0 \tag{A.19}$$

Grouping the constant term gives A_0:

$$A_0 = \frac{(\gamma-1)(\theta\xi+(1-\gamma)\mu)}{(1-\psi)\theta g_1} \tag{A.20}$$

$$\tag{A.21}$$

while A_1 is solved out from the quadratic equation:

$$2\sigma^2\psi^2A_1^2+(\theta g_1\frac{1-\psi}{1-\gamma}+2\sigma\psi(1-\gamma)FL')A_1+\frac{1}{2}\gamma(\gamma-1)=0 \tag{A.22}$$

Then we solve for dynamics of state price density:

$$\pi_t = \exp(\int_0^t f_J(C_s,J_s)ds)f_C(C_t,J_t) \tag{A.23}$$

Applying Itô's lemma

$$\frac{d\pi_t}{\pi_t} = df_J+\frac{df_c}{f_c}+\frac{1}{2}df_Jdf_J+df_J\frac{df_c}{f_c} \tag{A.24}$$

For the two related terms on the right hand side, notice that from (A.4) and the log-linear approximation:

$$f_J = (\theta-1)\beta G-\beta\theta \approx (\theta-1)(g_1\frac{1-\psi}{1-\gamma}(A_0+A_1y)+\beta+\xi)-\beta\theta = \xi_1-g_1\frac{1-\gamma\psi}{1-\gamma}A_1y \tag{A.25}$$

$$f_C = \beta\frac{G}{C}(1-\gamma)J = \frac{(1-\gamma)J}{W} = \beta^{\psi\gamma}\exp(\frac{1-\gamma\psi}{1-\gamma}(A_0+A_1y))C^{-\gamma} \tag{A.26}$$

Then

$$df_J = -g_1 \frac{1-\gamma\psi}{1-\gamma} A_1((\sigma^2 - 2\kappa y_t)dt + 2\sigma\sqrt{y_t}FdW_t) \tag{A.27}$$

$$\frac{df_C}{f_C} = -\gamma\frac{dC}{C} = -\gamma(\mu dt + \sqrt{y_t}LdW_t) \tag{A.28}$$

$$df_J df_J = (2g_1 \frac{1-\gamma\psi}{1-\gamma} A_1\sigma)^2 y dt \tag{A.29}$$

$$df_J \frac{df_C}{f_C} = 2g_1 \frac{1-\gamma\psi}{1-\gamma} A_1\sigma\gamma y F L' dt \tag{A.30}$$

We thus obtain the state price density:

$$\frac{d\pi}{\pi} = -r_t dt - (2g_1 \frac{1-\gamma\psi}{1-\gamma} A_1\sigma\sqrt{y}F + \gamma\sqrt{y}L)dW_t \tag{A.31}$$

where $r_t = g_1 \frac{1-\gamma\psi}{1-\gamma} A_1(\sigma^2 - 2\kappa y_t) - \gamma\mu + 2(g_1 \frac{1-\gamma\psi}{1-\gamma} A_1\sigma)^2 y + 2g_1 \frac{1-\gamma\psi}{1-\gamma} A_1\sigma\gamma y F L'$[1]

Now define $\lambda_t = \lambda_0 + \lambda_1 x_t = \lambda_0 + \lambda_1\sqrt{y_t}$, and replace into (A.31), after imposing restrictions on F and L, we can obtain:

$$\frac{d\pi}{\pi} = -r_t dt - \lambda_t F dW_t \tag{A.32}$$

Thus the model-implied state price density matches the form in the main article.

We study the equilibrium risk premium of consumption claim in this economy, applying Itô's lemma on (A.10):

$$d(\log\frac{C}{W}) = \frac{dC}{C} - \frac{dCdC}{2C^2} - \frac{dW}{W} + \frac{dWdW}{2W^2} = 2\frac{1-\psi}{1-\gamma}A_1 dy \tag{A.33}$$

Suppose the wealth evolves according to the process:

$$\frac{dW}{W} = \mu_t dt + \sigma_t H dW_t \tag{A.34}$$

where H is $1\times m$ vector with $HH' = 1$. Equation (A.33) and (A.34) together imply

[1]Note that the short rate process is now quadratic in state, thus not consistent with equation (4.2.9). However, the specification of short rate process is not essential for the predictability results

the expressions for μ_t and $\sigma_t H$:

$$\sigma_t H = \sqrt{y_t} L - 4\frac{1-\psi}{1-\gamma} A_1 \sigma \sqrt{y_t} F \tag{A.35}$$

$$\mu_t = \mu - \frac{1}{2} y_t + \frac{1}{2}\sigma_t^2 - 2\frac{1-\psi}{1-\gamma} A_1 (\sigma^2 - 2\kappa y_t) \tag{A.36}$$

Under continuous time framework, the expected return for the consumption claim is:

$$E_t(\frac{dW_t}{W_t}) + \frac{C_t}{W_t} dt = r_t dt - E_t[\frac{d\pi_t}{\pi_t}\frac{dW_t}{W_t}] \tag{A.37}$$

The risk premium is:

$$\begin{aligned} E_t[\frac{d\pi_t}{\pi_t}\frac{dW_t}{W_t}] &= -\lambda_t K H' \sigma_t dt = -\lambda_t K(\sqrt{y_t} L' - 4\frac{1-\psi}{1-\gamma} A_1 \sigma \sqrt{y_t} F' \\ &= 4\frac{1-\psi}{1-\gamma} A_1 \sigma \frac{\lambda_t^2 - \lambda_t \lambda_0}{\lambda_1} K F' - \frac{\lambda_t^2 - \lambda_t \lambda_0}{\lambda_1} K L' \end{aligned}$$

Notice from (A.31) that the instantaneous variance of log state price density is linear function y_t and therefore λ_t^2, therefore we find that indeed conditional variance of log SDF forecasts the stock risk premium.

5.3.4 Accuracy of the particle filter

Since Forex-specific factor is crucial in our analysis, and it is obtained through the particle filtering, it's of great importance to ensure the accuracy of the filter. We simulate 1000 sample paths using parameter estimates in Table 4.1 and 4.2, with the same length as the data sample. then we implement the particle filters on the simulated data. We calculate the ratio of mean absolute error to the true state for each sample path to measure the difference between those two. The average filtering error from 1000 simulations is about 0.35%. To illustrate the accuracy of filtering more directly, we plot the true state and filtered state from a randomly selected sample in Figure A.6.

Figure A.6. Performance of the particle filter

The figure plots the filtered and true state from an arbitrarily selected set of simulated data.